INTRA-HOUSEHOLD INTERACTIONS

MOVING BEYOND THE INDIVIDUAL: ACTIVITY-BASED MODELING OF TIME USE AND TRAVEL BEHAVIOR INCORPORATING INTRA-HOUSEHOLD INTERACTIONS

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ABSTRACT

The activity-based approach to the study of travel behavior implies a shift in focus from discrete trips to activities. A fundamental tenet of this approach is that individuals, when making their own activity-travel decisions, tend to interact with other members within a household. However, most activity-based research to date has been conducted at the individual level, but not at the household level. It is now well recognized that incorporating intra-household interactions is crucial to the development of improved activity-based models, which allow for more accurate travel demand forecasts and policy evaluations. In this context, the studies described in this dissertation have been conducted to explore several critical issues that have remained largely neglected in past studies.

One such issue is the identification of joint participation in activity and travel episodes, due to the fact that most activity-travel surveys have failed to collect information on involved persons. In this dissertation, an integrated spatio-temporal GIS toolkit is initially developed to automatically identify and visualize (3D) joint activity/travel episodes. Such identification makes it possible to uniquely and directly incorporate intra-household interactions into studies of activity/travel behavior. The research described in this dissertation utilizes the 2003 CHASE (Computerized Household Activity Scheduling Elicitor) survey collected in the Greater Toronto Area. Several aspects of activity/travel behavior are investigated. First, quantitative models are developed and estimated for investigating household activity time use patterns while capturing intra-household interactions. Second, the dynamics of household time use patterns are explored through descriptive analysis and structural equations models. Finally, the household activity decision-making process is further delved into with a focus on the planning priority of joint activities. Overall, the research presented in this dissertation makes important contributions to activity-based time use and travel behavior research: (1) technically, the developed GIS toolkit is helpful to reduce costs of processing large activity-travel datasets; and (2) theoretically, the empirical results presented will form the basis toward the development and implementation of an improved activity-based model.

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To my parents, I say thank you for your unwavering support, encouragement and belief. I would also like to thank my sisters and my brother for their always being there for me. Finally, and most importantly, I am indebted to my husband, Guoshun, for his unwavering support and love. This dissertation is not only my achievement but his as well.

PREFACE

This dissertation is a compilation of four main research papers that have either been accepted, submitted (or in preparation) for publication in peer-reviewed journals. For this reason, there is some degree of repetition among the chapters, particularly in their introduction and data set. The various research activities including literature review, programming, data preparation, statistical analysis, interpretation of results and writing of the papers were completed by the dissertation author. However, Dr. Darren Scott is co-author of the four papers. His contribution included guidance on research ideas and methods, critical appraisal of manuscripts and editorial reviews. Another co-author of the fourth paper provided me the data source. The research papers are as follows:

Chapter 2:

Kang H., D.M. Scott (2008) *An integrated spatio-temporal GIS toolkit for exploring intra-household interactions.* Transportation 35: 253-268.

Chapter 3:

Kang H., D.M. Scott (2008) *Joint or solo: a structural equations model of household activity time allocation patterns.* Transportation (under review)

Chapter 4:

Kang H., D.M. Scott (2008) *Modeling day-to-day dynamics in individuals' activity time use considering intra-household interactions.* Transportation Research Record (under review)

Chapter 5:

Kang H., D.M. Scott, S. Doherty (2008) *An investigation of planning priority of joint activities in the household activity scheduling process.* Transportation Research Record (under review)

TABLE OF CONTENTS

LIST OF TABLES

CHAPTER 2

CHAPTER 3

CHAPTER 4

CHAPTER 5

LIST OF FIGURES

CHAPTER 2

CHAPTER 4

APPENDIX

Chapter 1 Introduction

1.1 Justification of Research Topic

The activity-based approach to urban travel forecasting dates back to the mid 1970's, which has rapidly demonstrated its potential for replacing state-of-the-practice travel demand models– namely, the Urban Transportation Modeling Systems (UTMS). This new approach implies a shift in focus from trips to activities assuming that most travel is not an end in itself but a means to bridge activities that are separated in time and space. A fundamental tenet of the activity-based approach is its focus on sequences or patterns of activity/travel behavior in the context of space, time and interpersonal constraints rather than discrete trips (Kitamura, 1996). The interpersonal constraint, different from the other two, has received relatively limited attention in the activity analysis literature, as indicated by Goulias and Kim (2005) and Srinivasan and Bhat (2005). Activities and travel involving other household members require its participants to fit periods of joint episodes into individual schedules while their own needs and those of others are considered (Gliebe and Koppelman, 2002; Scott and Kanaroglou, 2002). In other words, the spatio-temporal constraints imposed upon one member's activities could influence the activities of other members within a household (Kang and Scott, 2008; Shaw and Wang, 2000). Therefore, the activity-based approach creates the need to "obtain a wide variety of household information and to take account of linkages among trip making and activity behavior for all household members" (Jones et al., 1990).

Household members interact in different ways when making their activity/travel decisions. Specifically, Srinivasan and Bhat (2005) summarize four general types of intra-household interactions: sharing of household maintenance obligations, joint engagement in other activities and travel, offering pick-up and drop-off services to household members with restricted mobility, and sharing the use of family vehicles. The motivations of joint participation proposed by Townsend (1987) have been widely acknowledged. These include efficiency, companionship and power/altruism. Activities and travel involving other household members result from a collective decision-making process that requires its participants to fit periods of joint episodes into individual schedules while considering their own needs and those of others (Gliebe and Koppelman, 2005).

The advantages of analyzing intra-household interactions are summarized by Fujii et al (1999) and Bhat and Pendyala (2005). First, time spent with other household members (particularly, with children) in joint activities is important to individual feelings of satisfaction and in their decisions of time allocation into joint and solo activities (Fujii et al., 1999). Second, insight into intra-household interactions will benefit other related research such as the activity scheduling process of household members, and its dynamic pattern between weekday and weekend. Explicit recognition of joint episodes in the underlying scheduling process is crucial to improving activity-based models, by providing more accurate travel-demand forecasting (Fujii et al., 1999), and capturing potential responses to certain policy changes in land-use and transportation systems (Bhat and Pendyala, 2005). This is because a transport policy will impact an individual behavior not only directly but also indirectly by changing household behaviors (Kato and Matsumoto, 2006; Scott and Kanaroglou, 2002). In recent years, recognition of the importance of intra-household interactions has produced a growing body of research (Bradley and Vovsha, 2005; Carrasco and Miller, 2006; Gliebe and Koppelman, 2002; Gliebe and Koppelman, 2005; Goulias and Hensen, 2006; Hollander and Prashker, 2006; Scott and Kanaroglou, 2002; Srinivasan and Athuru, 2005; Srinivasan and Bhat, 2006).

Despite this, however, several issues have not been well addressed. One such issue concerns the identification of joint activity/travel episodes. In most studies, this is done by stipulating the same purpose/travel mode, exact location (in the case of activities), exact timing and exact duration, which we, like Gliebe and Koppelman (2002) before us, argue may be too restrictive. Simply put, some episodes that are joint in reality may be misclassified as independent when using such criteria. The following example is a case in point. Two householders (a couple) drive separately to the same restaurant for dinner. However, one arrives ten minutes earlier than the other. In this instance, according to the criteria outlined above, the householders' dinner episodes would be classified as independent simply because they do not overlap with one another in terms of timing. To identify all occurrences of joint episodes, such as the one above, more flexible criteria must be developed. Furthermore, such criteria must be automated via computer-based technology to reduce the costs (both time and money) associated with processing large household-based, activity/travel data sets to identify joint episodes. Geographic information systems (GISs) are ideally suited to this task given their unique ability to store, process, analyze and display vast quantities of georeferenced data. Moreover, they have a proven track record in activity-based research (Kwan, 2004; Scott, 2006).

Once joint activity episodes are identified, the task remains to understand activity patterns into which elements of joint participation (i.e., intra-household interactions) are incorporated. Activity time allocation concerns the amount of time spent pursuing particular activity types over a certain time period such as a day. In this research, one of the challenges is to explore household time allocation patterns in which joint activities are interspersed with independent activities. Most previous empirical studies devoted to household activity time allocation behavior have not differentiated joint episodes from solo episodes (e.g., Bhat and Misra, 1999; Golob and McNally, 1997; Lu and Pas, 1999). In other words, intra-household interactions are explored, at most, indirectly. For those which have, identification of joint activity participation is often confounded by differences in reporting between household members (Gliebe and Koppelman, 2002). As indicated by Gliebe and Koppelman (2002), inconsistent reporting, along with other ambiguity involved in a survey data set, will underestimate the number of joint episodes. Therefore, the choice of different sets of criteria (restrictive vs flexible) might have an impact on research findings regarding household activity time allocation patterns. This represents a pioneering research effort.

Another issue which has been largely unexplored is the variability of activity patterns. Almost all activity-based studies have employed a single-day sample for analysis of activity time allocation patterns (Bhat et al., 2005). One implicit assumption is that activity decisions are uniform and independent from one day to the next (Bhat et al., 2005), which obviously does not reflect real activity decision patterns. For instance, unlike work, which is conducted regularly, certain activities such as grocery shopping or recreation activity tend to have a longer cycle for participation (Bhat et al., 2005). In addition, interactions between household members might vary over time as well, which might show different patterns (e.g., on weekdays vs. on weekends), due to different flexibility of the schedule (Zhang et al., 2005). As a result, it is important to develop an understanding of how intra-household interaction varies or repeats over time, in the household time allocation context. Variability analysis, which investigates the extent to which our activity-travel decisions give rise to consistent activity/travel patterns (Pas, 1987), is another focus of this research.

The last issue concerns the activity scheduling process, by which individuals decide which activities to conduct, where, when, for how long, sometimes with whom, and the transport mode used undertake their activities. Household members interact in many ways to coordinate their schedules (Arentze and Timmermans, 2004; Miller and Roorda, 2003). Obvious examples of household interaction in the scheduling process include generation of joint activity episodes, household vehicle sharing and the coordination necessary for care of the children (Miller and Roorda, 2003). However, in most operational models, intra-household interactions have been incorporated, at best, by making static assumptions. For instance, in TASHA (Miller and Roorda, 2003), it is assumed that joint activities tend to be pre-planed. Furthermore, the priority of planning joint activities is assumed to be same for all involved household members. The research focus here is to investigate whether such assumptions hold true through empirical studies.

1.2 Research Objectives

The fundamental motivation for this dissertation is to address the unexplored issues discussed above by explicitly identifying and integrating intra-household interaction into activity-based travel models. Specifically, the dissertation focuses on four main aspects of activity-based research. First, an integrated spatio-temporal GIS toolkit is developed to automatically identify and visualize (3D) joint activity/travel episodes. Such identification makes it possible to uniquely and directly incorporate intra-household interactions into studies of activity/travel behavior. Second, quantitative models are developed and estimated for investigating household activity time allocation patterns while capturing intra-household interactions. Third, the dynamics of household time allocation patterns are explored through descriptive analysis and structural equations models. Finally, the household activity decision-making process is further delved into with a focus on the planning priority of joint activities. Details concerning each of these objectives are found in the following section.

Overall, the research presented in this dissertation makes important contributions to activity-based time use and travel behavior research. Technically, the developed GIS toolkit is helpful to reduce the costs (both time and money) associated with the processing of large activity-travel datasets. Theoretically, the empirical results presented in these studies will form the basis toward the development and implementation of an improved activity-based time use and travel behavior model. Ideally, the model with explicitly incorporating intra-household interactions could better evaluate impacts of policy actions and meet expectations concerning the accuracy and reliability of forecasts (Scott and Kanaroglou, 2002). For example, multiple out-of-home activities may be predicted for household members by models which do not differentiate joint activities from independent activities, when, in fact, only one exists. Another example would be teleworking males tend to increase out-of-home joint activities with their family members, but decrease out-of-home independent maintenance, in comparison with other males who work outside home. This means that teleworking could be introduced to promote joint participation by household members, in so doing reducing traffic congestion.

1.3 Dissertation Contents

The reminder of the dissertation is organized as follows. Chapter 2 reports on the development and implementation of an integrated spatio-temporal GIS toolkit using an object-oriented GIS design, in the ArcGIS® 9.1 environment. This is the first household-based toolkit designed to explore intra-household interactions. Specifically, two tools comprise the toolkit. The first tool, Space-Time Coincidence Analyst, identifies joint activity/travel episodes undertaken by household members. The core of this tool is that a set of flexible criteria[1] is developed for classifying episodes as either joint or independent. In addition, the toolkit also allows a comparison of important attributes (e.g., frequency, timing, duration and composition of activity purposes) of joint and independent activities between restrictive criteria[2] and flexible criteria. The second tool, Space-Time Path Visualizer, not only displays space-time paths for household members, but also shows joint episodes undertaken by any two household members together. The toolkit can be applied to any household-based, activity/travel data set so long as required information is specified by the user.

In Chapter 3, it is argued that intra-household interactions should be explicitly incorporated into studies of household time allocation patterns. The spatio-temporal GIS toolkit is adopted to differentiate joint activities by two household heads (husband and wife) from their independent activities, based upon flexible criteria and restrictive criteria respectively. This study adds to the body of knowledge on the complicated relationships among household activity time allocation patterns and socio-demographic variables. Furthermore, our research moves beyond previous research efforts by differentiating joint activities from solo activities, which explores intra-household interactions more directly and explicitly. The findings have important implications for formulating transportation policies

1 The flexible criteria include same location, same activity type/mode (most aggregated), and flexible time (e.g., a 10-minute difference in the starting time and a 10-minute difference in the ending time).

2 The restrictive criteria include same location, same activity type/mode (most disaggregated), and same time.

that enhance people's quality of life by understanding their activity time allocation patterns. This study also provides insights into the impact of different classification criteria on empirical findings regarding household time allocation patterns.

Chapter 4 investigates variability in the activity context, namely, interpersonal and intrapersonal variability through descriptive analysis and structural equations modeling. To our knowledge, this study represents the first effort to explore variability in household time allocation while differentiating joint activities from independent activities. Two main findings are reported in this chapter: 1) there is evidence of variability in household-based time allocation patterns and variability in the impacts of socio-demographics on such pattern; and 2) the variability between weekdays and weekends is bigger than at the daily scale. The variability in household time allocation needs to be addressed for activity-based travel modeling to develop more accurate travel forecasting.

Chapter 5 focuses the planning priority of joint activities in the activity scheduling process. The activity scheduling process describes which activities to conduct, by whom, for how long, at what time and location, and by what mode. Activity priority has been suggested as an important dimension in the construction of scheduling models, particularly as a determinant for the sequencing and choice of activities. The growing recognition of intra-household interactions has led to a rapid expansion of research and development of technologies that can incorporate such interactions into activity-based scheduling models. Within such models, joint activities, however, have been dealt with, at best, by assuming that they tend to be planned first and simultaneously for their participants. Specifically, two important issues regarding the planning priority of joint activities are investigated in this chapter, which are: 1) the extent to which joint activities are pre-planned in the household scheduling process; 2) the disparity demonstrated by female and male household heads during their planning process. Overall, the simulation results indicate that not all joint activities are planned in advance, and the planning priority of joint activities is different for their participants (i.e., husband and wife), although their planning decisions are highly correlated.

Finally, Chapter 6 concludes the dissertation with a summary of contributions to deepening the understanding of household activity studies regarding individual and joint participation in activity and travel episodes. Also suggestions for extensions and future research are discussed in this chapter.

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Chapter 2 An Integrated Spatio-temporal GIS Toolkit for Exploring Intra-household Interactions

2.1 Introduction

A fundamental tenet of the activity-based approach is its focus on sequences or patterns of activity/travel behavior in the context of space, time and interpersonal constraints rather than discrete trips (Kitamura, 1996). In other words, the spatio-temporal constraints imposed upon one member's activities could influence the activities of other members within a household (Shaw and Wang, 2000). Therefore, the activity-based approach creates the need to obtain all household information and also to take into account the linkages among trip making and activity behavior for all household members (Jones et al., 1990).

Household members interact in different ways when making their activity/travel decisions. Specifically, Srinivasan and Bhat (2005) summarize four general types of intra-household interactions: sharing of household maintenance obligations, joint engagement in other activities and travel, offering pick-up and drop-off services to household members with restricted mobility, and sharing the use of family vehicles. The motivations of joint participation proposed by Townsend (1987) have been widely acknowledged. These include efficiency, companionship and power/altruism. Activities and travel involving other household members result from a collective decision-making process that requires its participants to fit periods of joint episodes into individual schedules while considering their own needs and those of others (Gliebe and Koppelman, 2005). Insight into intra-household interactions will benefit other related research such as the activity scheduling process of household members, and its dynamic pattern between weekday and weekend. Explicit recognition of joint episodes in the underlying scheduling process is also crucial to improving activity-based and tour-based travel demand forecasting models, thus making them even more capable of capturing responses to policy changes in land-use and transportation systems (Bhat and Pendyala, 2005).

In recent years, recognition of the importance of intra-household interactions has produced a growing body of research (Bradley and Vovsha, 2005; Carrasco and Miller, 2006; Gliebe and Koppelman, 2005; Gliebe and Koppelman, 2002; Goulias and Hensen, 2006; Hollander and Prashker, 2006; Scott and Kanaroglou, 2002; Srinivasan and Athuru, 2005; Srinivasan and Bhat, 2006). Despite this, however, several issues have not been well addressed. One such issue concerns the identification of joint activity/travel episodes. In most studies, this is done by stipulating the same purpose/travel mode, exact location (in the case of activities), exact timing and exact duration, which we, like Gliebe and Koppelman (2002) before us, argue may be too restrictive. Simply put, some episodes that are joint in reality may be misclassified as independent when using such criteria. The following example is a case in point. Two householders (a couple) drive separately to the same restaurant for dinner.

However, one arrives ten minutes earlier than the other. In this instance, according to the criteria outlined above, the householders' dinner episodes would be classified as independent simply because they do not overlap with one another in terms of timing. To identify all occurrences of joint episodes, such as the one above, more flexible criteria must be developed. Furthermore, such criteria must be automated via computer-based technology to reduce the costs (both time and money) associated with processing large household-based, activity/travel data sets to identify joint episodes. Geographic information systems (GISs) are ideally suited to this task given their unique ability to store, process, analyze and display vast quantities of georeferenced data. Moreover, they have a proven track record in activity-based research (Kwan, 2004; Scott, 2006).

Another issue concerns the geovisualization (visualization of geographic information) of intra-household interactions in 3D. Previous research efforts, at most, displayed co-located activities in space and time, which are not necessarily joint due to lack of a third criterion – activity type (Buliung and Kanaroglou, 2006). As noted by Kwan (2000), geovisualization of activity/travel data is an effective exploratory tool that often leads to more focused research. Moreover, she argues that geovisualization can assist in formulating realistic computational or behavioral activity/travel models.

In response to the issues noted above, this chapter reports on the development of an integrated spatio-temporal GIS toolkit that facilitates the exploration of intra-household interactions by identifying and visualizing (3D) joint activity/travel episodes. Past research relating to these topics is reviewed briefly in the following two sections. Next, it presents the spatio-temporal GIS design underlying the toolkit. This is followed by a brief discussion concerning its implementation in ArcGIS (version 9.1), a GIS software package developed and distributed by ESRI. The usefulness of the toolkit is demonstrated via an empirical study using the TAPS (Toronto Activity Panel Survey) 2002-03 data set. The results from the study are documented. The chapter concludes by summarizing both the functionality and limitations of the toolkit.

2.2 Identification of Joint Episodes

In the past, many activity/travel surveys have failed to collect information on involved persons. This has been especially true for the large-scale, trip-based surveys that underpin urban travel demand models around the world. Although this appears to be changing, even if collected, such information, without proper validation, may not be reliable due to recall errors by sampled individuals. Furthermore, in existing household-based, activity/travel surveys, the attributes of episodes (i.e., activity type/travel mode, start time, end time, duration, location) that are joint in nature may be reported differently by household members involved when, in fact, they should be the same. Given these issues, care must be exercised when identifying joint episodes for research. In essence, such episodes should be identified based on information that is both reliable and readily available in most surveys. That is to say, criteria must be developed for classifying entire episodes or parts thereof as either joint or independent. Strictly speaking, joint episodes should meet conditions of joint--

in-purpose/mode (activity type/travel mode), joint-in-location, and joint-in-time. Purpose/mode, location and time are all readily available in activity/travel surveys of the past and the present, although the level of detail concerning their reporting can vary from one survey to the next. Gliebe and Koppelman (2005) suggest that joint episodes should be identified by comparing reported starting and ending times, origin and destination locations, trip purposes, travel modes, driver/rider status and passenger relationships for each household member's daily trip records. However, inconsistent reporting about starting and ending times, different perceptions of activity purposes by household members, along with other ambiguities involved in a survey data set, will likely underestimate the number of joint episodes. While this problem may be addressed to some extent in future surveys by improving survey techniques to acquire and validate explicitly joint activities and travel among household members, the techniques may prove costly to implement in terms of time and money. Moreover, undue burden will necessarily be placed on survey respondents. One means to overcome issues concerning the identification of joint activity/travel episodes in past, present and future surveys is to develop "more proximate matching criteria to include joint episodes that are not reported identically by household members, but have enough in common to be safely categorized as joint" (Gliebe and Koppelman, 2002).

Miller (2005) describes a partial solution for identifying joint episodes by using time geography's bundle concept, which requires that during a time interval ($t_B^{'}, t_B^{''}$) two individual space-time paths must share the time interval, which means that a path can only start (C_S) or end (C_E) at the interval boundaries or outside the interval – that is, $C_S \le t_B^{'} \wedge C_E \ge t_B^{''}$. This condition helps relax the joint-in-time criterion without requiring the same timing by two paths. Also, both paths must be proximal for the interval ($t_B^{'}, t_B^{''}$).

In the context of information and communication technologies (ICT), Yu (2006) uses the bundle concept to identify four patterns of human interaction using space-time paths: co-location in space, co-location in time, co-existence in both space and time, and no co-location in either space or time. A GIS-based tool is developed to detect these forms of human interaction. Unfortunately, however, it is implemented for individuals rather than households, and thus, by design, is unable to identify joint activity/travel episodes. Also, as mentioned earlier, identification of such episodes requires comparison of a third criterion – namely, activity type or mode. The tool does not incorporate such a comparison.

In an earlier effort aimed at detecting joint trips in the Mobidrive data set, Singhi (2001) developed a C++ program that compared trips of household members based on a set of criteria including study code, city code, day of reporting and trip mode. In addition, to account for recall or encoding errors, the temporal gap in arrival and departure times had to be less than five minutes. This interval was chosen over others (i.e., zero and 10 minutes) because, apparently, it detected the maximum number of joint trips[3]. The only possible shortcoming of this approach as applied to the Mobidrive data set is that the joint-in-location

3 It is unclear how a five-minute gap in arrival and departure times can produce more joint trips than a 10-minute gap, as reported in Singhi (2001). One would expect either the same number of trips or more trips, not fewer trips.

criterion is not guaranteed. Quite simply, location is defined very broadly in terms of two German cities – Halle and Karlsruhe. Moreover, it is unclear from Singhi's work whether location applies to the origin or destination of the trip, or both. At the same time, however, the program can be easily enhanced to overcome this possible shortcoming by comparing location at a higher level of detail.

It is clear from the literature that there exists an urgent need to advance the identification of joint activity/travel episodes. To ensure that all occurrences of joint episodes are accounted for, it is necessary to relax restrictive criteria (i.e., same timing, specific activity type/travel mode) to allow for issues such as inconsistent reporting of starting and ending times, and different perceptions of activity purposes and travel modes by household members, along with other ambiguities involved in a survey data set. We refer to this new set of criteria as flexible (i.e., proximate timing, general activity type/travel mode).

2.3 Space-time Path Visualization

In many studies, to facilitate the exploration of human activity/travel behavior, individual daily space-time paths were represented as lines connecting various destinations by using 2D maps or graphical methods (Chapin, 1974). One limitation of such representation is that certain important attributes of activities and trips such as timing, duration and sequencing failed to be well kept (Kwan, 2000). Some recent efforts attempt to incorporate these attributes by developing more effective database management approaches (Shaw and Wang, 2000; Wang and Cheng, 2001). In other words, at the data organization level, the aim is to store and manage efficiently all attributes associated with the data such that redundancy is minimized while retaining complex relationships among data.

Geovisualization (visualization of geographic information) is the use of concrete visual representations and human visual abilities to make spatial contexts visible (Maceachren et al., 1999). A space-time path is essentially a linear feature, describing an individual's movements in physical space over time (see Figure 2.1a). Unlike the other approaches mentioned above, it allows for a comprehensive presentation of information on spatio-temporal characteristics of an individual's actions, including the starting/ending times and locations of activities, the duration and the sequence of activities. In other words, the space-time path concept offers an effective approach to analyzing individuals' activities in a spatio-temporal context (Miller, 2005). The concept of "bundle" (see Figure 2.1b) has recently been recognized as an efficient way to illustrate interactions within households (Hagerstrand, 1970; Miller, 2005), which contributes to an understanding of household roles and responsibilities (Miller, 2005). Bundling often occurs when two or more space-time paths converge for a shared activity, implying that the paths are vertical and the individuals are stationary in space. However, it also happens that two separate paths bundle during movement, examples of which include two individuals carpooling or taking a bus together (Miller, 2005). With the ability of GIS to implement the space-time path and bundle concepts, and the availability of more activity/travel diary data, GIS-based 3D geovisualization has been widely recognized as a potential approach to exploring spatio-temporal characteristics of human activity/travel patterns (Kwan, 2000; Pipkin, 1995). The advantages of using 3D geovisualization for such exploration are summarized by Kwan (2000).

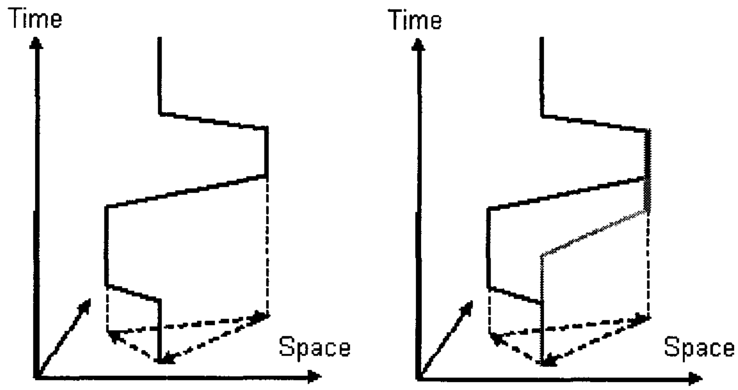

Figure 2.1 a) A space-time path; b) Space-time bundle

Buliung and Kanaroglou (2006) developed a household trajectories tool, which can automatically construct household space-time path data structures for all householders over a period of time. At the daily scale, xy coordinates of activity sites visited by household members are used to define locations in 2D while the timing information associated with these activities define locations in time. However, the geovisualization function demonstrated is limited to individual space-time paths, but not joint paths, the pattern of which will enhance our understanding of intra-household interactions. Another thing to note is that their tool is tied to the data set they used, which is the 1994/1995 Portland Household Activity and Travel Behavior Survey. Therefore, adaptation is needed when applying the tool to other activity/travel surveys.

2.4 Spatio-temporal GIS Design

As discussed above, the identification of joint episodes should meet three criteria: joint-in-purpose (activity type/travel mode), joint-in-time and joint-in-location, which, for reasons given, can be restrictive. Therefore, flexible criteria have to be developed to include all joint occurrences of human activity/travel behavior within a household, by relaxing one or all of the above criteria. For the joint-in-location criterion, one possible way to make it flexible is through buffering. However, this might overestimate the number of joint episodes by mistakenly classifying different places as the same one. Therefore, the flexible criteria developed here focus on the relaxation of timing and activity type/travel mode[4] by assuming that all joint episodes should share the same location. Conceptually, the ideas of restrictive and flexible criteria used for identifying joint episodes are illustrated in Figure 2.2. In the left

4 For timing, relaxation means that our flexible criteria allow a slightly different gap in starting/ending times. When it comes to activity type/travel mode, relaxation refers to activities/modes that belong to different types if applying more disaggregate classification schemes, but share the same type/mode if applying more aggregate classification schemes.

cube (see Figure 2.2a), only the cell below the shaded surface represents absolutely "true" joint activity/travel if using restrictive criteria. In the right cube (see Figure 2.2b), joint episodes could at most exist in the four cells, right below the shaded surface in the right cube (Figure 2.2b)[5]. Steps 1 to 3 show how to implement the criteria.

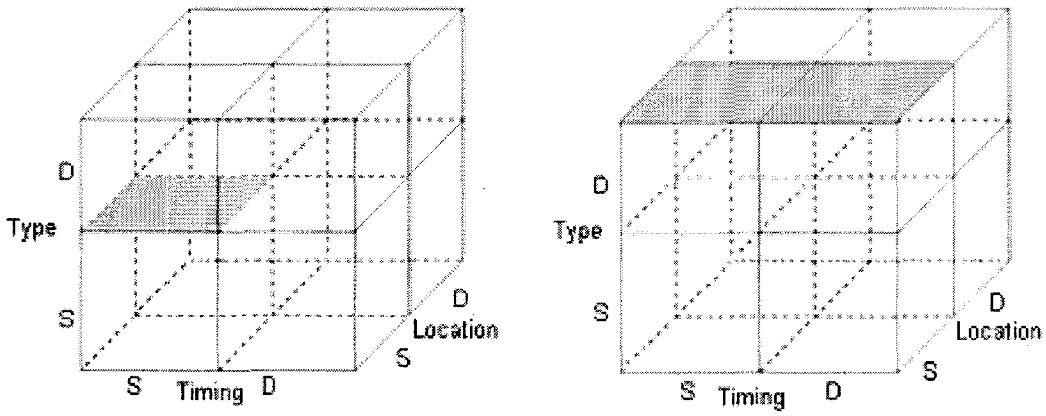

Figure 2.2 Using a) restrictive criteria and b) flexible criteria to identify joint activity/travel in a space-time context (S = same; D = different)

5 When it comes to type, the "D" refers to activities belong to different types if applying more disaggregate classification schemes, but share the same type if applying more aggregated classification schemes.

Step 1: To meet the criterion of joint-in-location, a method called Intersect is used to identify all activity/travel episodes with the same location (Yu, 2006). Due to lack of a 3D intersect approach, all activity and travel episodes have to be analyzed respectively in the 2D plane.

Step 2: Figure 2.3a and 2.3b illustrate how the temporal overlap of potential joint activity and travel episodes are identified respectively when the joint-in-location criterion is met. A_1, A_2, B_1, and B_2 represent the starting and ending times for person A (black line) and person B (grey line), respectively. t refers to the temporal overlap or joint time period shared by two people. t_1 and t_2 indicates the temporal gap of the starting times and that of ending times by two persons, respectively. For illustration purposes only, the joint activity and joint travel episodes are each represented as two separate lines (i.e., one per individual) when in fact they overlap in space. The temporal overlap only happens when $A_1 \leq B_2$ and $B_1 \leq A_2$. This means that the starting time of an activity by one person is no later than the ending time of an activity by another person. Furthermore, the actual temporal overlap, or the lasting time period of this joint activity starts from the moment of maximum (A_1, B_1), and ends at minimum (A_2, B_2) (Yu, 2006). Joint travel, different from joint activities, has to meet the constraining condition, which requires that the temporal gap, t_1 and t_2 should be less than a small value, if not equal to 0. Such relaxation might help reduce the impact of recalling errors by sampled individuals. Although Singhi (2001) proposed applying a 5-minute interval to a six-week travel survey conducted in Germany (Axhausen et al., 2002), in our approach, the decision is left to the user, who knows the accuracy of his/her data.

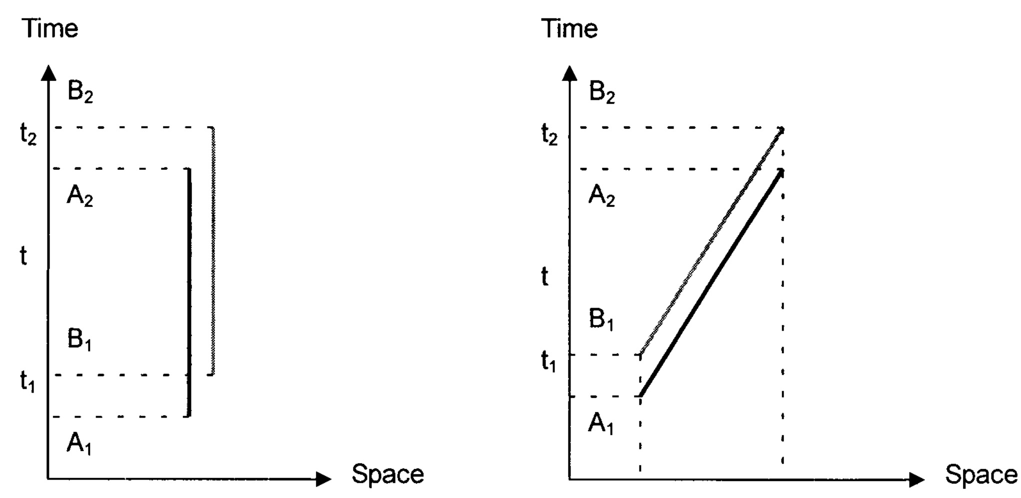

Figure 2.3 a) Joint activity episode; b) Joint travel episode

Step 3: Besides the location and temporal criteria, activity type/travel mode is an imperative part of the flexible criteria. If the classification scheme used in a survey is too detailed, sampled individuals might classify the same activity into different types, due to different perceptions or recalling. For instance, a couple goes shopping together – the husband might label the activity as simply shopping, while the wife might label the same activity as shopping for clothes. Consequently, this activity cannot be classified as joint. One way to relax this criterion is reclassifying disaggregate activity types/travel modes into more generic groups (in the above example, shopping for clothes is reclassified as shopping). One example of such a classification scheme, which is employed in our empirical analysis, is: meals, work/school, family obligations, drop-off/pick-up, shopping, services, active recreation, entertainment, and social.

2.5 Implementation of the Design in ArcGIS

ArcGIS and ArcObjects are chosen as the development environment for our tool for several reasons. First, a geographic information system (GIS) is able to integrate a large amount of geographic data from different sources and then solve spatial problems (Kwan 2000). Second, the ArcScene module in ArcGIS, which supports representation and visualization of 3D spatial features, is amenable to the 3D data structure (2D space + time) required by the time geography framework with time replacing altitude or elevation. Furthermore, it is very easy to exploit the available visualization functions embedded in the ArcScene platform such as zooming in, zooming out, rotating, and so on. Finally, ArcObjects offers a programming environment to develop new spatio-temporal analysis functions (Yu 2006).

The integrated space-time GIS approach is implemented through two tools in the ArcGIS 9.1 software platform: one is called Space-Time Coincidence Analyst, which is embedded in ArcMap, and the other is called Space-Time Path Visualizer, which is embedded in ArcScene. In ArcMap, intra-household interactions (represented as joint activity/travel episodes) are identified by using both the traditional restrictive criteria and our newly developed flexible criteria. Joint episodes are then exported as a database file according to household types (i.e., single with children, couple with children, and couple without children). ArcScene is used to visualize individual space-time paths, analyze relationships of such paths at the household level and then visualize joint episodes undertaken by household members. Visual Basic for Applications (VBA) programs with ArcObjects is used in our toolkit to generate the customized user interfaces and functions. The toolkit incorporates functions for generating/visualizing patterns of human activity/travel, which are represented as individual space-time paths in 3D, and functions for identifying/visualizing intra-household interactions for any two household members, which are represented as joint space-time paths in 3D. Furthermore, our tool is able to extract the exact joint time period for those joint activities by two household members who do not have the same starting times and/or ending times. The rest of this section describes how these two tools and their functions are implemented in

ArcGIS and how they help explore the spatio-temporal characteristics of human activities and interactions.

2.5.1 Space-Time Coincidence Analyst Tool

The Space-Time Coincidence Analyst toolkit identifies joint activity/travel episodes for any two household members using both the traditional restrictive criteria and our newly developed flexible criteria. Joint episodes are exported as a database file according to household types (i.e., single with children, couple with children, and couple without children), specified by the user. This toolkit has five components, which are: 1) Import File, 2) Joint Analysis, 3) Join, 4) Query, and 5) Open ArcScene, which builds a connection to the ArcScene window. Details about each component are described in Appendix A.

2.5.2 Space-Time Path Visualizer Tool

This Space-Time Path Visualizer tool has three components: 1) Import File. 2) Individual Path Creation, and 3) Joint Path Creation. The first function this tool provides is creating an individual space-time path for each household member in 3D. Another function supported by this tool is creating joint paths by multiple householders, which is decomposed into two interrelated steps: the identification and visualization of joint episodes in 3D. The pattern of these joint episodes in space and time can serve to better understand intra-household interactions and/or generate hypotheses for further testing. However, the user can be easily overwhelmed by the data displayed given the limits of human visual discrimination.

2.6 Empirical Study

To demonstrate the usefulness of the toolkit, we conduct an empirical study to compare several key attributes (i.e., frequency, starting/ending time and duration) of individual and joint episodes using restrictive and flexible criteria[6], respectively. The TAPS (Toronto Activity Panel Survey) 2002-03 data set is used for this purpose. Specifically, the data were obtained from a Computerized Household Activity Scheduling Elicitor (CHASE) survey conducted in Toronto, Ontario. The data set contains 474 adults residing in 240 households. In total, these sampled adults undertook 28,680 uniquely labeled activities over the course of one week, each of which is associated with attributes[7].

Table 2.1 compares the number of joint episodes identified by different criteria. When using restrictive criteria (same time and same activity type/travel mode), only 1,795 joint activity and 470 joint travel episodes are found, compared to 8,055 and 737 episodes, respectively, when using flexible criteria. The occurrences of joint activities and joint trips when using flexible criteria account for 44.5% and 16.1% of total activity and trip episodes in the data set. Within this line of research, several studies have been conducted (Gliebe and

6 A more detailed explanation about restrictive and flexible criteria can be found in the notation of Table 2.1.

7 These include: 1) location: out-of-home activities, which represented 25.6% of the total activities, and in-home activities; 2) 67 specific activity types (e.g., housewares shopping, clothes shopping), which are summarized into 10 generic group labels (e.g., shopping); 3) 31 specific travel modes (e.g., SUV), categorized into 4 generic group types (e.g., automobile).

Koppelman, 2005; Singhi, 2001; Vovsha et al., 2004). For example, applying restrictive criteria to a two-day travel diary collected in Seattle, Washington, Gliebe and Koppelman (2005) indicated that, out of 26,492 out-of-home episodes, 29% is identified as either joint activity and/or a shared ride by two adult householders. However, shared episodes between children and one adult household member were identified as independent due to their research purpose. Using the same criteria, Vovsha et al. (2004) reported that joint travel represents a significant percentage of total travel (limited to home-based motorized trips only), close to half of the mid-Ohio tours, and more than one-third of the New York tours, about 75% of which is made by members of the same household. Here joint travel is measured at the tour level, which includes fully joint tours and partially joint tours (i.e., joint at one directional leg only). The work by Singhi (2001), to our knowledge, represented one of the early efforts to relax the joint-in-time criterion, by allowing for a 5-minute temporal gap for both starting times and ending times. It is reported that, in two German cities, Karlsruhe and Halle, 22% of the total trips undertaken by individuals within a household are joint. One thing that should be noted, however, is that values reported in the above studies are not comparable due to different units of analysis (i.e., episode vs. tour) and different research foci (i.e., adults only vs. all householders) across different regions.

Table 2.1 Comparison of the number of joint episodes using different criteria

	Type/mode[8]	Same time	Flexible time[9]	Difference
Joint activity	Specific	1,795 (357)[10]	6,599 (787)	4,804 (430)
	Generic	1,848 (359)	8,055 (815)	6,207(456)
	Difference	53 (2)	1,456 (28)	
Joint travel	Specific	470	721	251
	Generic	474	736	262
	Difference	4	15	

8 Specific type/mode refers to the most disaggregated activity type/travel mode, while generic type/mode refers to a more aggregated activity type/travel mode. For instance, in our empirical study, the specific classification scheme includes 67 activity types and 32 travel modes, and the generic scheme includes 10 activity types and 4 travel modes.

9 Flexible time for joint activity requires that the starting time of one activity is earlier than the ending time of the same activity undertaken by another person. Flexible time for joint travel allows for a 10-minute difference in the starting time and a 10-minute difference in the ending time reported by different individuals.

10 () represents the number of out-of-home activities when using different criteria.

We also calculated the proportion of joint activities that take place out-of-home. Out of all joint activities, 10.1% (815) occur outside the home when using the flexible criteria compared to 19.89% (357) when using the restrictive criteria. The proportion of out-of-home joint activities is much lower than that of in-home joint activities. Two reasons are suggested for this: one is that householders are more likely to participate in joint activities in the home; the other is related to the dominance of in-home activities collected in the original survey data set (74.4%).

Such numerical differences between restrictive and flexible criteria are also illustrated in Figure 2.4, which displays how the spatio-temporal features of human activity/travel behavior are visualized in ArcScene. At the bottom of the figure, the black dots represent the participant household locations in Toronto, and grey lines represent the highway network. As an example, on the right side of the figure is the space-time path of a husband (the thin grey line) and a wife (the thin black line) on one particular day. The two attribute tables show records of joint episodes undertaken by the couple together, when using flexible criteria (above) and restrictive criteria (below), which are also, respectively, represented as thick grey lines, and thick black lines in this figure. From this figure, we find that, in the bottom right-hand corner, the two lines overlap each other, which means that this joint episode (i.e., night sleep at the beginning of the day) is effectively identified by both criteria. In the morning, the wife leaves for work, but the husband undertakes some recreational activities near the home and then picks up their children in the afternoon. After work, the wife drives to meet her husband at a friend's place and attend a social event together, which is the second joint activity identified for the couple using flexible criteria (see the upper table). This joint activity, along with six other episodes (i.e., meals, entertainment, and night sleep), is not identified by restrictive criteria (see the lower table).

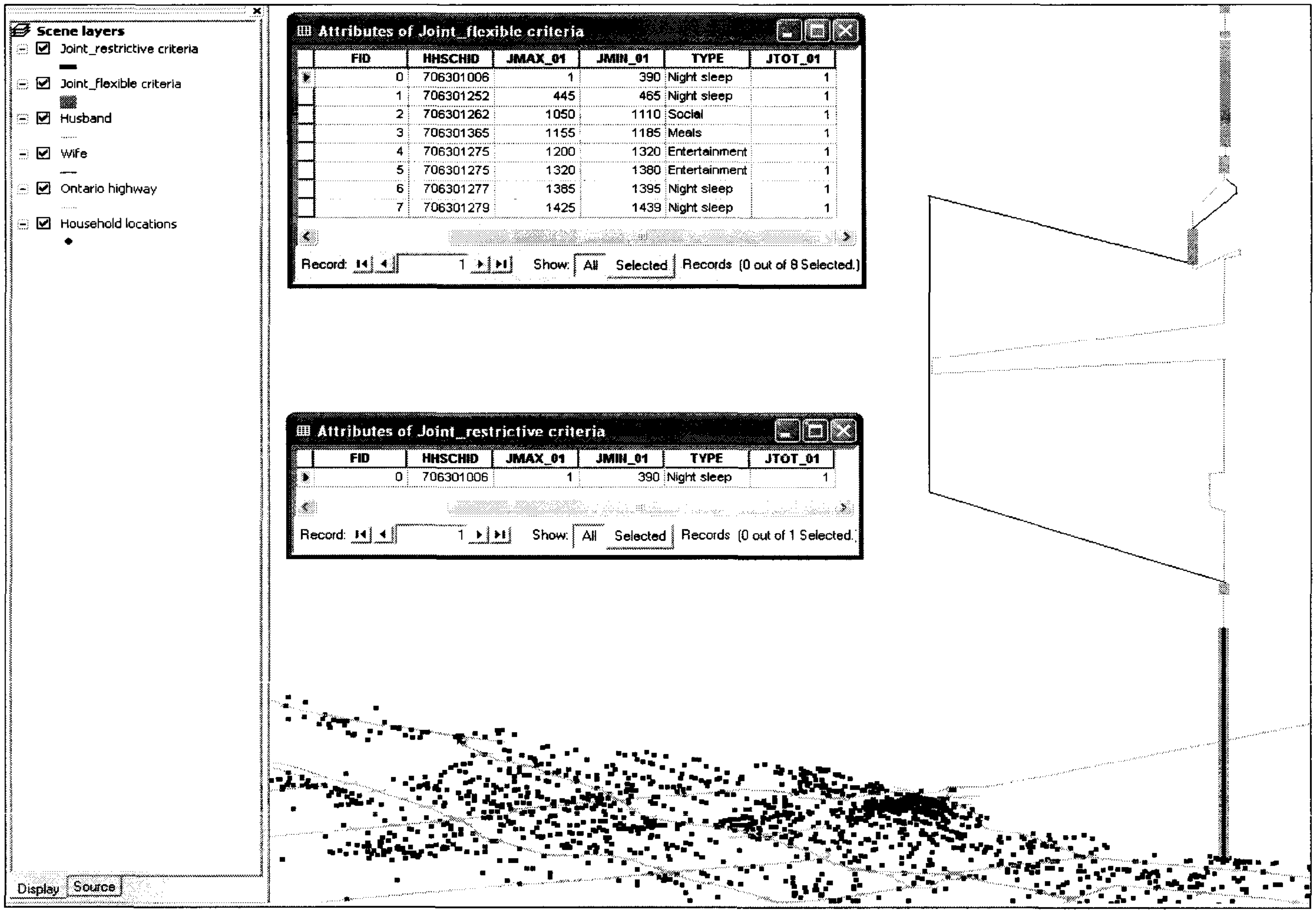

Figure 2.4 Visualization of two space-time paths using the space-time path visualizer tool in ArcScene

The functions supported by the Space-Time Path Visualizer tool are not limited to illustrating the differences between flexible and restrictive criteria, however. The tool also aids in understanding human activity patterns in several ways. First, the tool, combined with some visualization functions offered by ArcScene (i.e., zooming in, zooming out, panning and rotating), provides a dynamic and interactive environment within which human activity/travel behavior patterns can be examined from different angles. For instance, the researcher can change the symbols of space-time paths (i.e., color and width), or query data (i.e., focusing only on sub-groups of the whole data set, such as females, retired persons, etc.), with the impacts of such changes being seen quite easily. This is more functional compared with the conventional representation approaches (e.g., 2D) described earlier. Second, by retaining the spatial and temporal characteristics of the original data, the Visualizer can be used to identify complex relationships (i.e., "bundles") among household members within the scope of human vision (Kwan, 2000).

Table 2.2 describes the variation in several key attributes of joint and independent activities identified using restrictive and flexible criteria: frequency, starting time, ending time and duration (minutes). These attributes are selected for comparison because of their significant impacts on understanding urban activity-travel patterns, which has two implications. First, by accounting for joint out-of-home activities, predictions of activity-travel demand models are more likely to be accurate (Scott and Kanaroglou, 2002). Second, attributes of independent and joint activities, such as timing and duration, are helpful to capture potential responses to certain operational strategies (e.g., advanced traffic control strategies), and evaluate the effectiveness of some transportation demand management (TDM) measures (e.g., congestion pricing) (Bhat and Steed, 2002). Recently, aware of these implications, some modeling efforts have focused on the timing (Arentze and Timmermans, 2004; Bowman and Ben-Akiva, 2001) and duration of daily activities (Bhat, 1996; Ettema et al., 1995; Schwanen, 2004; Yee and Niemeier, 2000). However, little research has been conducted in the context of independent/joint activities/travel.

Table 2.2 Comparison of key attributes of joint vs. individual episodes using flexible and restrictive criteria

Type	Criteria	Frequency	Starting time				Ending time				Duration
		per household	(minutes)				(minutes)				(minutes)
		Mean	Mean	Median	Skewness	Kurtosis	Mean	Median	Skewness	Kurtosis	Mean
Joint episodes	Flexible	31.4	795.3	960	-0.42	-1.26	916.1	1050	-0.20	-1.50	120.7
	Restrictive	7.4	812.9	1020	-0.53	-1.10	945.1	1080	-0.25	-1.46	132.3
Independent episodes	Flexible	88.1	816	840	-0.37	-0.65	923.1	960	-0.25	-0.93	107
	Restrictive	112.1	807.9	845	-0.42	-0.77	924.5	985	-0.23	-1.09	116.5

Furthermore, to explore extensively the distribution patterns of starting/ending times, we examined some other statistical measures, including the median, skewness, and kurtosis. The median, as a measure of central tendency, is not as sensitive to outlying values (i.e., extremely high or low values) as the mean, but shows a similar trend with it. A skewness value of zero represents a symmetric distribution (normal). The results indicate that, for both independent and joint episodes, the distributions of the starting and ending times when using flexible criteria are slightly less skewed than when using restrictive criteria, although each has a left tail (i.e., negative sign). Kurtosis is a measure of the extent to which observations cluster around a central point. Its value is 0 for a normal distribution, while a negative value indicates the observations cluster less and have shorter tails. For joint episodes, the Kurtosis statistics indicates that the starting and ending times by flexible criteria are less clustered than those by restrictive criteria, a trend which is converse for independent episodes.

Figure 2.5 presents the different compositions of joint activities in terms of their purposes based on different criteria. We find that for both criteria, similarly, the role of night sleep is predominant (45.7% when using flexible criteria vs. 44.1% when using restrictive criteria) over other activity types. However, compared with flexible criteria, restrictive criteria report a larger proportion of meals, but lower proportions of household obligations and entertainment. One possible reason for this disparity is that people tend to report certain types of joint activities (i.e., meals) more consistently than others (i.e., watching TV, email, relaxing, etc.). The proportions of other seven activity types remain at around the same level for both criteria.

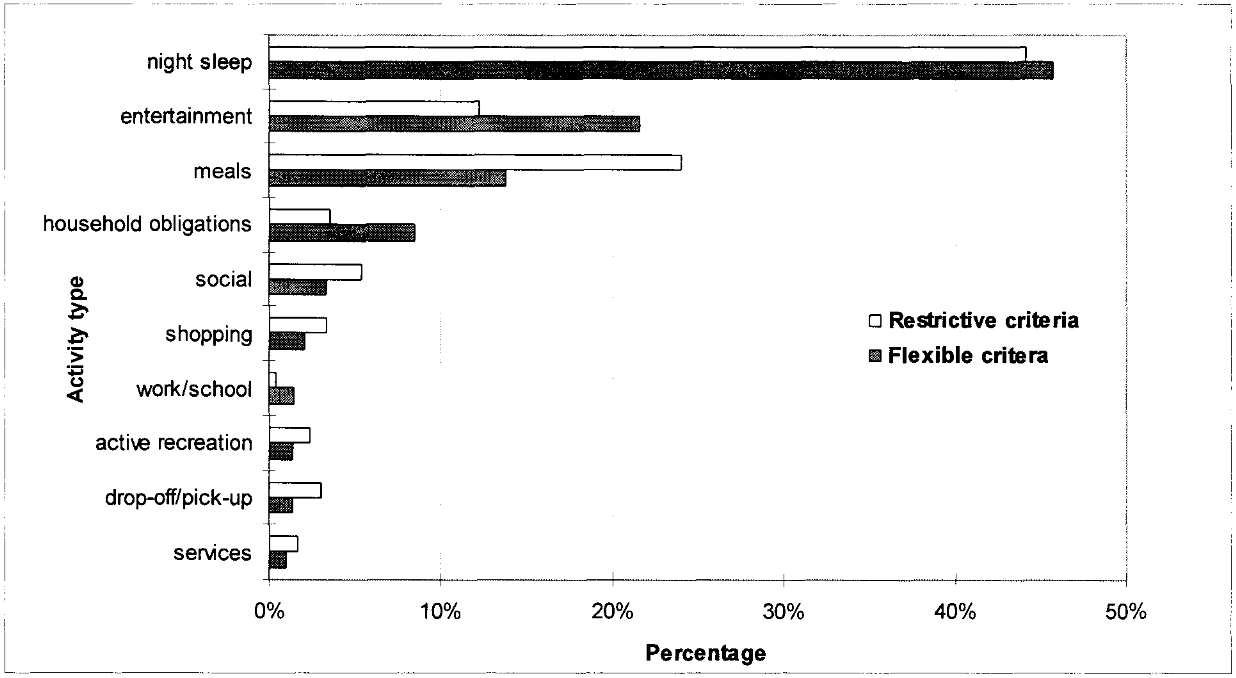

Figure 2.5 Comparison of the activity type composition of joint activity episodes using flexible criteria and restrictive criteria, respectively

2.7 Conclusions

As argued at the beginning of this chapter, recognition of the importance of intra-household interactions has recently produced a growing body of research, aiming to enhance our understanding about this phenomenon. Several issues, however, have not been well addressed by those studies. First, the widely used method to identify joint episodes by requiring the same purpose (activity type), exact location, timing and duration might be too restrictive to include all occurrences of joint episodes. The second issue is the visualization of intra-household interactions in 3D. Previous research efforts, at most, displayed co-located activities in space and time (Buliung and Kanaroglou, 2006; Yu, 2006), which cannot be referred to as joint activities due to lack of a third dimensional criterion – for example, activity type (Buliung and Kanaroglou, 2006).

Our research moves beyond past studies of exploring intra-household interactions by developing the first household-based, spatio-temporal GIS toolkit, which is implemented in the environment of ArcGIS 9.1. This toolkit includes two tools, namely, the Space-Time Coincidence Analyst tool and the Space-Time Path Visualizer tool, which are complimentary, but independent. In other words, the two tools, collectively, support functions including the identification of joint episodes, the representation of space-time paths, and spatio-temporal relationships of these paths in 3D, or they can be used independently, depending on the user's purpose. Furthermore, the toolkit can be applied to any household-based, activity/travel data set so long as required information is specified by the user.

Our toolkit also allows a comparison of important attributes of joint and independent activities between restrictive and flexible criteria. Those key attributes include frequency, timing, duration and composition of activity purposes. Our empirical study, which applies the toolkit to the TAPS (Toronto Activity Panel Survey) 2002-03 data set, suggests that considerable variation exists in the number of joint activity/travel episodes identified using different classification criteria. Specifically, when using restrictive criteria (i.e., same timing, specific activity type/travel mode), only 2,265 joint activity/travel episodes are identified compared to 8,791 when using more flexible criteria. In turn, our results show that certain key attributes for independent and joint activity/travel episodes (i.e., frequency per household, starting time, ending time and duration) also vary under the different classification criteria. We also compared the composition of joint episodes when using different criteria, which has direct implications for how to improve designs of future activity/travel surveys.

The design presented in this chapter provides a useful toolkit for exploring comprehensively intra-household interactions. However, one limitation is that only intra-household interactions between any two household members can be captured by this framework. Although it sounds workable in theory, complexity increases exponentially when extending our toolkit from the two-person dimension to three or more-person dimensions. At the same time, however, this limitation can be easily overcome by the researcher through follow-ups. For instance, if the researcher is interested in joint episodes undertaken by three family members, a simple query (i.e., JTOT_01=1 and TOT_02=1) can be built easily and quickly either in ArcGIS or Microsoft Access. Another limitation is that we have not applied our toolkit to other data sets, which might exhibit some slightly different results, although similar trends are expected. In general, we suggest that conclusions should not be derived from this study without first considering these limitations.

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Chapter 3 Joint or Solo: a Structural Equations Model of Household Time Allocation Patterns

3.1 Introduction

Focusing on sequences or patterns of activity/travel behavior, in the context of space, time and interpersonal constraints, is one fundamental tenet of the activity-based approach (1996). The interpersonal constraint, different from the other two, has received relatively limited attention in the activity analysis literature, as indicated by Goulias and Kim (2005) and Srinivasan and Bhat (2005). Activities and travel involving other household members require its participants to fit periods of joint episodes into individual schedules while their own needs and those of others are considered (Gliebe and Koppelman, 2002; Scott and Kanaroglou, 2002). In other words, the spatio-temporal constraints imposed upon one member's activities could influence the activities of other members within a household (Kang and Scott, 2008; Shaw and Wang, 2000).

The advantages of analyzing intra-household interactions are summarized by Fujii et al (1999) and Bhat and Pendyala (2005). First, time spent with other household members (particularly, with children) in joint activities is important to individual feelings of satisfaction and in their decisions of time allocation into joint and solo activities (Fujii et al., 1999). Second, explicit recognition of joint episodes is crucial to improving activity-based models, by providing more accurate travel-demand forecasting (Fujii et al., 1999), and capturing potential responses to certain policy changes in land-use and transportation systems (Bhat and Pendyala, 2005). This is because a transport policy will impact an individual behavior not only directly but also indirectly by changing household behaviors (Kato and Matsumoto, 2006; Scott and Kanaroglou, 2002). Recognition of the importance of intra-household interactions has recently produced a growing body of research (Bradley and Vovsha, 2005; Gliebe and Koppelman, 2002; Goulias and Hensen, 2006; Scott and Kanaroglou, 2002; Srinivasan and Bhat, 2006).

However, most previous empirical studies devoted to intra-household interactions have not differentiated joint episodes from solo episodes. In other words, intra-household interactions are explored, at most, indirectly. One exception is the work by Gliebe and Koppelman (2002), who identified joint episodes by a set of criteria stipulating the same purpose/travel mode, exact location, timing and duration, which are too restrictive (Gliebe and Koppelman, 2002; Kang and Scott, 2008), in that some activities might still be joint although not completely meeting such criteria. One example would be that a couple drives separately to the same restaurant for dinner, but one arrives ten minutes earlier than the other (Kang and Scott, 2008). Furthermore, when analyzing household activity-travel records, identification of joint activity participation is often confounded by differences in reporting between household members (Gliebe and Koppelman, 2002). As indicated by Gliebe and

Koppelman (2002), inconsistent reporting, along with other ambiguity involved in a survey data set, will underestimate the number of joint episodes. Therefore, more flexible criteria[11] have to be applied to identify all occurrences of joint activity/travel behavior (Gliebe and Koppelman, 2002; Kang and Scott, 2008). The choice of different sets of criteria (restrictive vs flexible) might have an impact on research findings regarding intra-household interactions.

The primary objective of this chapter is to capture intra-household interactions and intra-person interactions simultaneously, and the impacts of socio-demographics and the choice of different classification criteria (i.e., restrictive vs. flexible) on such interactions. Past research relating to these topics is reviewed briefly in four aspects: what relationships are explored, what variables are used, what methods are adopted, and their key findings. This is followed by a description of the data used. Then the paired sample *t*-tests and the structural equations modeling method are adopted to capture interactions as described above. The results from the study are documented. Finally, conclusions and research directions are summarized.

3.2 Literature Review

As seen in a recent special issue of Transportation (Volume 32 Issue 5), as well as couple of studies found elsewhere (Sener and Bhat, 2007), recognition of the importance of intra-household interactions has recently produced a growing body of research (Bradley and Vovsha, 2005; Gliebe and Koppelman, 2002; Kato and Matsumoto, 2006; Scott and Kanaroglou, 2002; Srinivasan and Athuru, 2005; Srinivasan and Bhat, 2006). The review of earlier research about household time allocation models is pursued under four categories: what relationships are explored; what socio-demographics are accounted for; what modeling methods are adopted; and what are their key findings.

3.2.1 What Relationships are Investigated?

The most widely used activity typology was first employed by Reichman (1976): subsistence, maintenance and discretionary (or leisure). This is followed by many researchers (Bhat and Koppelman, 1993; 1999; Bhat and Misra, 1999; Golob and McNally, 1997; Jones et al., 1990; Lu and Pas, 1999). The reason for using this broad classification scheme is given by Golob and McNally (1997), who indicated that 'if more activity categories are used, there will be more parameters in the model, and accurate estimation of these parameters will require a larger sample size. These three categories are further differentiated regarding the in-home/out-of-home decision, and the weekday/weekend decision. The determination of whether an activity is pursued at home or away from home is important from the perspective of travel demand, because an in-home activity does not require travel, while an out-of-home one requires travel (Jones and Clark, 1988). The weekday/weekend decision is an important

11 These include same generic activity type (the more aggregated activity type), same location, and flexible timing (the starting time of one activity is earlier than the ending time of the same activity undertaken by another person), same activity type (the more aggregated activity type)

one since it is associated with when trips are made, which impacts traffic congestion (Bhat and Koppelman, 1993).

The work by Fujii et al. (1999), to our knowledge, represented one of the early efforts to classify all activities into joint and solo in the context of time allocation, by companion type and location type. However, relationships among different activity types are not investigated. Likewise, Gliebe and Koppelman (2002) classified all activities into six categories: out-of-home subsistence, out-of-home independent maintenance, out-of-home independent leisure, out-of-home joint maintenance, out-of-home joint leisure, and in-home. One limitation of such classification is that joint activities are identified based on restrictive criteria (i.e., same timing, specific activity type/travel mode). Such criteria, as discussed in the previous section, along with inconsistent reporting between household members, will underestimate the number of joint episodes. Another shortcoming of this study is that the relationship between joint and solo activities is, at most, indirectly captured by building error correlations across two household heads, while correlations between subsets of activities are not investigated (Gliebe and Koppelman, 2002) . To improve the performance of identifying joint episodes, Kang and Scott (2008) developed a set of flexible criteria to differentiate between joint and independent activities/travel for any activity/travel survey. This allows the identification of joint episodes more accurately and expediently.

3.2.2 What Socio-demographics are Accounted for?

The motivations of joint activity participation proposed by Townsend (1987) have been widely acknowledged, which include efficiency, companionship and power/altruism. The importance of each motivating factor is a function of activity types, household and individual socio-demographic characteristics, and work or school commitments (Gliebe and Koppelman, 2002). The relationship between these factors and joint activity-travel behavior has been explored by a number of researchers (Gliebe and Koppelman, 2005; Gliebe and Koppelman, 2002; Golob and McNally, 1997; Jones et al., 1983; Lu and Pas, 1999; Scott and Kanaroglou, 2002; Zhang et al., 2005). Among all the factors, Jones et al. (1983) found that joint episodes undertaken by a couple is significantly impacted by the presence of children. In particular, couples without children are more likely to pursue joint out-of-home non-work activities than couples with children. Other variables, such as age of the heads, number of workers, number of vehicles, household tenure, license, and vehicle status are also widely used in previous studies (Golob and McNally, 1997; Lu and Pas, 1999; Scott and Kanaroglou, 2002). In addition, Zhang et al. (2005) introduced total travel time of all the used travel modes, along with the variables mentioned above, to analyze married couples' task and time allocation behavior. To analyze gender-role based differences in time allocation, Cao and Chai (2007) introduced commute time and found that it influences both maintenance activity duration and leisure activity duration.

3.2.3 What Modeling Methods are Adopted?

According to Kato and Matsumoto (2006), recent studies in the context of intra-household interactions are classified into four types from a methodological viewpoint. The first approach is based on the discrete choice model system, which include Bradley and

Vovsha (2005), Scott and Kanaroglou (2002), and Srinivasan and Bhat (2005). The second approach is based on the time allocation model system. Zhang and Fujiwara (2006), Zhang et al. (2005), Kato and Matsumoto (2006) and Gliebe and Koppelman (2002) are included in this approach. The third approach is based on the computer simulation system (Meister et al., 2005). Finally, the fourth approach is based on the simultaneous equation system including Golob (2000), Golob and McNally (1997), Lu and Pas (1999), Fujii et al. (1999), and Simma and Axhausen (2001). Our model is also included in the fourth approach.

Structural equations modeling (SEM) is unique in its simultaneous representation of multiple relationships among a set of variables, where the same variable that is the outcome (dependent variable) in one set of relationships may be a predictor of outcomes (explanatory variable) in other relationships (Bagley and Mokhtarian, 2002). Many aspects of activity participation and travel have been modeled by SEM (Golob, 2003). They include: 1) relationships between activity and travel demand (Golob and McNally, 1997; Lu and Pas, 1999); 2) relationships between participating in different types of activities (Golob and McNally, 1997); and 3) feedbacks from travel time to activity time (Zhang et al., 2005). However, interactions among individuals, especially within the same household is more desirable, and, in some cases, may be crucial for travel-demand analysis and forecasting (Gliebe and Koppelman, 2002; Scott and Kanaroglou, 2002).

3.2.4 What are Previous Research Findings?

Intra-household interaction and intra-person interaction have received growing attention from researchers, in terms of activity participation and travel. Lu and Pas (1999), focusing on intra-person interactions, found that the duration of out-of-home subsistence is negatively related to the duration of out-of-home maintenance, recreation and other activities, as would be expected. On the other hand, van Wissen (1989) developed structural models to capture interactions between household heads in terms of their activity participation. He found that the work duration for the male was the primary factor in determining the activity patterns of both partners, while the employment status of the female did not have an impact on the male's non-work activity duration. More comprehensively, Golob and McNally (1997) investigated both intra-household and inter-person interactions.. However, most previous studies investigate intra-household and intra-person interactions without differentiating all activities into joint and solo. This is mainly attributable to the difficulty of identifying joint episodes more accurately and expediently, as discussed in the previous section. For reasons given above, little attention has been paid to relationships between joint and solo activities, relationships among types of joint activities, and relationships among types of solo activities.

Socio-demographics that influence intra-person interaction and inter-person interaction have been explored by a number of researchers (Fujii et al., 1999; Gliebe and Koppelman, 2002; Golob and McNally, 1997; Jones et al., 1983; Sener and Bhat, 2007; van Wissen, 1989). The presence of children, which is the primary factor in shaping intra-household interactions, reduces time allocation to joint activities by household adults (Chandraskharan and Goulias, 1999; Gliebe and Koppelman, 2002; Jones et al., 1983; Kostyniuk and Kitamura, 1983). The employment status of both adults has been found to have an impact on whether a joint activity originated from home or out of home (Kostyniuk and Kitamura, 1983). In addition, Fujii et al. (1999) and Gliebe and Koppelman (2002) found that auto ownership levels increase the propensity to allocate time to independent out-of-home non-work activities. Household tenure is another important factor of influencing human activity patterns. Golob and McNally (1997) found that female heads that have resided in their current home one year or less tend to travel more for discretionary activities. Other variables like, the education level of household heads, household location and day of week/season of year have also been found to have an impact on types of discretionary activities and with whom (Sener and Bhat, 2007).

3.2.5 Remarks

It is clear from the literature review that household activity time allocation behavior and the impacts of socio-demographic factors in such behavior have been of tremendous interest to transportation researchers. Earlier empirical studies explore interactions among different activity types (Bhat and Misra, 1999; Golob and McNally, 1997; Lu and Pas, 1999), which also have successfully lent insight into the importance of joint activity participation. However, to our knowledge, no research has been conducted to simultaneously capture intra-household interactions, intra-person interactions, and the impacts of socio-demographics on such interactions. This study adds to the body of knowledge on the complicated relationships among household activity time allocation patterns and socio-demographic variables. Furthermore, our research moves beyond previous research efforts by differentiating joint activities from solo activities, which explores intra-household interactions more directly and explicitly. This study also provides insights into the impact of different classification criteria on empirical findings regarding household activity patterns.

3.3 Data Source

The 2003 CHASE (Computerized Household Activity Scheduling Elicitor) survey used for this study was conducted in Toronto, Ontario. The data set contains 240 households, including 474 adults (Doherty and Miller, 2000). In total, these sampled adults undertook a total of 28,680 activity episodes during one week, each of which is associated with attributes[12]. Kang and Scott (2008) developed a set of flexible criteria to differentiate between joint and independent activities/travel for any household activity/travel survey. A preliminary analysis is conducted and the results suggest that considerable variation exists in the number of joint activity/travel episodes identified using different classification criteria. Specifically, when using restrictive criteria, only 2,265 joint episodes are identified compared to 8,791 when using more flexible criteria.

Similar to Golob and McNally (1997), we limit our analysis to married and unmarried male and female couples. After data processing, a final sample of 192 adults (96 couples) is identified. Our analysis focuses on out-of-home episodes only, mainly because of

12 These include: 1) location: out-of-home activities, which represented 25.6% of the total activities, and in-home activities; 2) 67 specific activity types (e.g., housewares shopping, clothes shopping), which are summarized into 10 generic group labels (e.g., shopping); 3) 31 specific travel modes (e.g., SUV), categorized into 4 generic group types (e.g., automobile).

the fact that an out-of-home episode requires travel, while in-home episode does not (Jones and Clarke, 1988). Meanwhile, our focus on the weekday (Monday-Friday) stems from the intense traffic congestion prevalent in most urban areas during the morning and evening commute periods (Gliebe and Koppelman, 2002). As noted by Gliebe and Koppelman (2002), the types of activities most likely to be pursued jointly are maintenance and leisure activities. This is supported by Kang and Scott (2008) who reported that only 1% of work/school activity is identified as joint by using flexible criteria. Based on this, we limit our consideration of jointness to maintenance and discretionary activities only. Finally, all out-of-home activities are classified into five categories according to companion type and activity attributes: mandatory, independent maintenance, independent discretionary, joint maintenance and joint discretionary (see Table 3.1). Activity duration was computed by summing the time spent on each category of activity over five weekdays. Since the classification of joint and solo is based on restrictive and flexible criteria, two different groups of variables are acquired from the same data set, which are respectively included into our analysis.

Table 3.1 The endogenous variables based on flexible and restrictive criteria

Flexible criteria	Restrictive criteria	Description
ManF	ManR	Total 5-weekday duration of out-of-home mandatory activity
Indep maiF	Indep maiR	Total 5-weekday duration of out-of-home independent maintenance activity
Indep disF	Indep disR	Total 5-weekday duration of out-of-home independent discretionary activity
Joint maiF	Joint maiR	Total 5-weekday duration of out-of-home joint maintenance activity
Joint disF	Joint disR	Total 5-weekday duration of out-of-home joint discretionary activity

Note: Man = mandatory, including work and school; Mai = maintenance, which includes household obligations, drop off/pick-up, shopping and services; Dis = discretionary, which includes meals, services, active recreation, entertainment, social and other; Indep = independent; F = Flexible; R = restrictive

3.4 Paired Sample *T*-tests

Paired sample *t*-tests were used to compare time allocation of all activity types classified by flexible and restrictive criteria. Some interesting time allocation patterns are demonstrated. As shown in Table 3.2, all differences are significant at the 0.05 level. On average, the durations of mandatory, independent maintenance, and independent discretionary are shorter, while those of joint maintenance and joint discretionary are longer, by using flexible criteria than by using restrictive criteria. It indicates that the choice of classification criteria has an impact on household activity time allocation patterns.

Table 3.2 Paired sample T-tests for time allocation (in minutes)

Activity	Mean			*p*-Value for
	Flexible criteria	Restrictive criteria	Difference	Flexible criteria vs. Restrictive criteria
Mandatory	1518	1599	-81	0.006
Independent maintenance	194	221	-27	0.000
Independent discretionary	237	294	-57	0.000
Joint maintenance	50	18	32	0.000
Joint discretionary	114	57	57	0.000

3.5 Structural Equations Modeling

SEM is used to simultaneously capture intra-household interactions, intra-person interactions, and the impacts of socio-demographics on such interactions. Following the matrix notation of Lu and Pas (1999), an SEM for observed variables can be defined as

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

where

B is $p \times p$ matrix of coefficients, representing the direct effects of endogenous variables on other endogenous variables;

Γ is $p \times q$ matrix of coefficients, representing the direct effects of exogenous variables on endogenous variables;

y is a $p \times 1$ vector of endogenous variables;

x is a $q \times 1$ vector of exogenous variables;

ζ is a $p \times 1$ vector of errors in the equations, with the standard assumption that ζ is uncorrelated with x.

In addition to B and Γ, Φ $(q \times q)$ is the covariance matrix of x, and Ψ $(p \times p)$ is the covariance matrix of ζ. As structural equations models are estimated using covariance (structure) analysis, the fundamental idea in estimating the model is that Σ, the population covariance matrix of observed variables x and y, can be expressed by the unknown parameters (B, Γ, Φ, Ψ). Then, these unknown parameters can be estimated through minimizing the discrepancies between the sample (observed) covariance matrix S and the population covariance matrix Σ (Lu and Pas, 1999).

We use the most commonly applied covariance analysis method, maximum likelihood (ML), not only because it converges more rapidly and the results are also easier to interpret compared with asymptotically distribution-free (ADF) (Golob and McNally, 1997; Kline, 2005), but also its properties have been thoroughly investigated with respect to the effect of violations from normality on biases of estimators, nonconvergence, and improper solutions as a function of sample size (Golob and Regan, 2002). ML estimation has been found to be robust against violations of multivariate normality. Two optimal models we estimated. One is based on flexible classification criteria (the flexible model), and the other one is based on restrictive classification criteria (the restrictive model). The complexity of both models is prescribed by their sample size (192). One rule of thumb is that the sample size should be at least ten times the number of free parameters used in the model (Hoogland and Boomsma, 1998; Kline, 2005).

AMOS 7.0 was employed to develop SEMs. AMOS provides many goodness-of-fit measures. The chi-square statistic, the basis of most other measures, tests the null hypothesis that the model is correct (i.e., it has a perfect fit in the population) (Kline, 2005). Ullman

(1996) suggests that the chi-square should be less than two times its degrees of freedom. If the associated p-value is larger than 0.05, the researcher would not reject the null hypothesis at the 0.05 level, and the larger the better (Golob, 2003). Other goodness-of-fit indexes include NFI (Normed Fit Index), GFI (goodness-of-fit index), CFI (comparative fit index), RFI (relative fit index) and IFI (Incremental Fit index). For these measures, values closer to 1 indicating a good fit, as suggested by Kline (2005), and Mokhtarian and Meenakshisundaram (1999).

For both the flexible model and the restrictive model, endogenous variables are the same, which are independent maintenance, independent discretionary, joint maintenance and joint discretionary. The exogenous variables used in two models grouped into: household attributes, individual attributes and others (travel time and work duration). The choice of variables is guided by previous literature and it is also constrained by data availability. Household attributes include household tenure, presence of children, household size and number of motorized vehicles. Individual attributes include age, gender, education level, employment status, job duration and income of both household heads. Work activity duration and travel time are input as exogenous variables since they tend to be mandatory and inflexible (Pendyala, 2003). Travel time was computed by summing the time spent on traveling for each type of activity. The final set of effective exogenous variables is listed in Table 3.3.

Table 3.3 The exogenous variables

Abbreviation	Exogenous variables (dummies)
H_tenure	1 = households living in the same residence 1 year or less; 0 = otherwise
H_kids	1 = households having 1or more kids (6 years old or younger); 0 = otherwise
Autoratio	1 = households with more than 1 car per adult; 0 = otherwise
F_age35	1 = female age younger than 35 years (inclusive); 0 = otherwise
F_age65+	1 = female age older than 65 years (inclusive); 0 = otherwise
M_age35	1 = male age younger than 35 years (inclusive); 0 = otherwise
M_age65+	1 = male age older than 65 years (inclusive); 0 = otherwise
F_workathome	1 = female teleworking; 0 = otherwise
M_workathome	1 = male teleworking; 0 = otherwise
T_travel >1hr	1 = if daily travel time longer than 1 hour, 0 = otherwise

Based on travel behavior theory and the literature review, there are two groups of relationships that are hypothesized: 1) relationships among endogenous variables, namely, intra-household and intra-person interactions. First, we expect a substituting relationship between independent and joint activities. Second, we hypothesize that there is a relationship among independent activities (i.e., independent maintenance and independent discretionary). Third, we expect to find that there is a relationship between joint activities (i.e., joint maintenance and joint discretionary); 2) relationships between endogenous variables and exogenous variables. First, we hypothesize that higher levels of employment, presence of children and auto availability will tend to reduce joint activity by two household heads.

Second, time spent in subsistence activity (work and school) reduces the amount of time available for maintenance and leisure activities where opportunities for joint participation are greatest. Last, longer travel time might reduce the likelihood of couples taking joint activities (Cao and Chai, 2007; Zhang et al., 2005).

3.6 Structural Equations Modeling Results

The SEM results for household activity time allocation patterns are presented in three parts. In the first part, we want to compare between the best flexible model and the best restrictive model. In the second part, the relationships among endogenous variables are discussed. Finally, I describe the relationships between endogenous variables and exogenous variables, which are further differentiated into the impact of exogenous variables on independent activities, and that impact on joint activities.

3.6.1 Model Performance Comparisons

Table 3.4 compares measures of fit for the two optimal models - the flexible model and the restrictive model. For the flexible model, the Chi-square value was 28.1 with 37 degrees of freedom. The likelihood ratio test statistics is associated with the null hypothesis that the estimated model is consistent with the observed sample variance-covariance matrix. This value corresponds to a probability value of $p = 0.854$, indicating that the model definitely cannot be rejected at the $p = 0.05$ level. The goodness-of-fit index (GFI) is 0.975 indicating that the overall fit of the model is excellent. Other measures of fit such as normed fit index (NFI = 0.858) and root mean square error of approximation (RMSEA = 0) are also found to be acceptable by model fit criteria for a SEM. For the restrictive model, most of measures of fit have the same or a lower value compared with those of the flexible model, which indicate a slightly worse fit. Therefore, we can say that the overall performance of the flexible model is better than that of the restrictive model, although both of them indicate a good fit.

Table 3.4 Comparison of measures of fit for the flexible and the restrictive model

Measures of Fit Index (N=192)	Flexible model	Restrictive model
Degrees of freedom	37	40
Chi-square	28.1	36.75
Chi-square/d.f.	0.759	0.919
p-value	0.854	0.617
Goodness-of-Fit Index (GFI)	0.975	0.967
Normed Fit Index (NFI)	0.858	0.814
Comparative Fit Index (CFI)	1.0	1.0
Root Mean Square Error of Approximation (RMSEA)	0.0	0.0
Akaike Information Criterion (AIC)	86.1	88.7

Table 3.5 presents the direct, indirect and total effects of the flexible SEM and the restrictive SEM for weekday out-of-home time allocation. Only those relationships significant at 0.05 level are displayed here, except for three of them marked with *, which are significant at 0.10 level. The bold numbers represent relationships, which are captured by the flexible model, but not captured by the restrictive model.

Table 3.5 Flexible structural equations model and restrictive structural equations model for weekday out-of-home time allocation

		Flexible model				Restrictive model			
Variables	**Standardized Effects**	**Joint disF**	**Joint maiF**	**Indep disF**	**Indep maiF**	**Joint disR**	**Joint maiR**	**Indep disR**	**Indep maiR**
H_kids	Direct	-0.148	-0.122	-	-	-0.182	-	-	-
	Indirect	-	-0.039	-	**0.017**	-	-0.028	-	-
	Total	-0.148	-0.161*	-	**0.017**	-0.182	-0.028	-	-
H_tenure	Direct	0	**0.194**	-	-	-	-	-	0.144
	Indirect	-	-	-	-0.021	-	-	-	-
	Total	0	**0.194**	-	-0.021	-	-	-	0.144
M_workhome	Direct	0.176	-	-	-	0.214	-	-	-
	Indirect	-	0.046	-	**-0.005**	-	0.033	-	-
	Total	0.176	0.046	-	**-0.005**	0.214	0.033	-	-
F_age65+	Direct	-	-	-	-0.111	-	-	-	-0.130
	Indirect	-	-	-	-	-	-	-	-
	Total	-	-	-	-0.111	-	-	-	-0.130
Autoratio	Direct	-	-	-	0.156	-	-	-	0.136
	Indirect	-	-	-	-	-	-	-	-
	Total	-	-	-	0.156	-	-	-	0.136
T_travel>1hr	Direct	-	**-0.157**	0.278	0.176	-	-	0.269	0.137
	Indirect	-	-	-	0.017	-	-	-	-
	Total	-	**-0.157**	0.278	0.193	-	-	0.269	0.137
Mand (F/R)	Direct	**-0.142**	-	-0.341	-0.479	-	-0.190	-0.406	-0.510
	Indirect	-	-0.037	-	0.004	-	-	-	-
	Total	**-0.142**	-0.037	-0.341	-0.475	-	-0.190	-0.406	-0.510
Joint_dis (F/R)	Direct	-	0.260	-	**-0.028**	-	0.155	-	-
	Indirect	-	-0.124	-	**-0.003**	-	-	-	-

	Total	-	0.136	-	**-0.031**	-	0.155	-	-
Joint_mai (F/R)	Direct	-	-	-	**-0.224**	-	-	-	-
	Indirect	-	-	-	**-**	-	-	-	-
	Total	-	-	-	**-0.224***	-	-	-	-

Note: * represents the regression coefficient is significant at the 0.10 level; all other variables significant at the 0.05 level. The bold numbers represent those effects which are captured by the flexible model, but not by the restrictive model;

(-)Variable not included in model

Generally speaking, regression effects of the flexible model appear consistent with estimates of the restrictive model in terms of signs and scale. However, there are some differences that need to be addressed. One interesting disparity is that for the flexible model, shorter household tenure (1 year or less) has a positive impact (0.194) on joint maintenance, but a negative impact (-0.021) on independent maintenance. However, for the restrictive model, there is only a positive impact (0.144) on independent maintenance. If we take a closer look at the composites (direct and indirect effects) of the total negative impact of shorter house tenure on independent maintenance, we find that it comes indirectly from the negative relationship of joint maintenance and independence maintenance. Furthermore, the negative coefficient is trivial compared to the positive impact (-0.021 vs. 0.144)) on independent maintenance. In reality, it is reasonable to assume that shorter household tenure would cause more maintenance activities, given the fact that new movers need spend more time on activities such as household obligations. Another disparity is that the flexible model is able to capture more relationships (see the bold numbers in Table 3.5). Such relationships include: the positive impact of presence of children on independent maintenance, the positive impact of shorter household tenure on joint maintenance, the negative impact of males working at home on independent maintenance, the negative impact of travel time on joint maintenance, the negative impact of mandatory on joint discretionary, of joint discretionary on independent maintenance, as well as the negative impact of joint maintenance on independent maintenance.

3.6.2 Household Activity Time Allocation

Both models offer very plausible results with respect to household time allocation, and most of them are found to be consistent with past literature (Golob and McNally, 1997; Kuppam and Pendyala, 2001; Lu and Pas, 1999). However, as discussed above, the flexible model is able to capture more relationships than the restrictive model. Therefore the following discussion is focusing on the flexible model.

The endogenous variables used in the two models are the same, which are durations of out-of-home independent maintenance, out-of-home independent discretionary, out-of-home joint maintenance and out-of-home joint discretionary. As expected, there is a trade-off between joint maintenance and independent maintenance, and more importantly, the direction from joint maintenance to independent maintenance is more significant than otherwise. This can be explained by the high priority of joint activities over independent activities. The model also indicates presence of a significant positive relationship between joint maintenance and joint discretionary, which means that people who are more inclined to take part in joint maintenance activities outside the home may also exhibit a greater tendency to participate in joint out-of-home recreation. This finding is quite consistent with that by Kuppam and Pendyala (2001). Another finding with regard to interdependence among activity participation is that joint discretionary is negatively related to independent maintenance. This finding can be explained by the previous findings: more joint discretionary leads to more joint maintenance, which otherwise decreases independent maintenance. Therefore, there is a negative relationship between joint discretionary and independent maintenance. In addition, individuals' work activity duration negatively influences their respective maintenance activity duration and discretionary activity duration, whether independent or joint with their partners. In other words, the effects of the work activity duration on time allocation essentially represent time constraints. These findings are also consistent with Golob and McNally (1997). From the above discussions, we can see that, differentiating all activities into independent and joint, allows us to deepen our understanding about household time allocation patterns, by providing some insightful interaction between household members.

The effects of sociodemographic characteristics are also consistent with earlier studies (Golob and McNally, 1997; Kuppam and Pendyala, 2001; Lu and Pas, 1999). Couples with children (6 years old or younger) are more inclined to undertake out-of-home independent maintenance activities, but are less likely to undertake out-of-home joint maintenance and joint discretionary activities. The negative impact of children on out-of-home discretionary activity (without differentiating between independent and joint) has been reported by Bhat and Misra (1999). Our finding that the presence of children reduces the propensity of household adults to spend time on joint activities together is also consistent with previous studies (Gliebe and Koppelman, 2002; Jones et al., 1983). This might be attributable to mobility constraints imposed by the presence of young children on couples.

It is interesting that high car ownership level (with more than one car per adult) increases out-of-home independent maintenance activities. There is some previous empirical studies backing to this funding (Bhat and Misra, 1999; Fujii et al., 1999; Gliebe and Koppelman, 2002; Scott and Kanaroglou, 2002). This is because a higher vehicle availability provides more opportunity and flexibility for out-of-home activity participation (Bhat and Misra, 1999). Furthermore, we find that females at a retired age are less likely to undertaken out-of-home independent maintenance activities than those who are younger. Finally, our estimates are in line with other studies in suggesting that income does not appear to have an impact on allocation of out-of-home time into independent and joint activities (Bhat and Misra, 1999; Kitamura et al., 1996).

Our study is of practical values in that it can be used to evaluate the impacts of certain policy actions. For instance, we find that males who work-at-home are more likely to take part in out-of-home joint maintenance and out-of-home joint discretionary, but are less likely to take part in out-of-home independent maintenance relative to males who work outside home. We also find that shorter traveling time is associated with longer duration of joint maintenance, but shorter duration of independent maintenance and independent discretionary. This suggests that, if travel time is shortened, then at least a part of that time savings will be spent on joint activities. These insights are essential for the development of robust travel behavior models that are sensitive to a host of transportation policy scenarios (Scott, 2002; Vovsha et al., 2003)

3.7 Discussion and Conclusion

SEMs were used to investigate out-of-home time allocation of household adults. The model is unique in its simultaneous representation of intra-household interactions, intra-person interactions and their socio-demographic factors. Also, our research moves beyond past studies of exploring intra-household interactions by differentiating joint activities from independent activities, which allows us to deepen our understanding about household time allocation patterns. Furthermore, the study suggests that choosing different classification criteria for identifying joint activities has an impact on the model performance and research findings.

Overall, our research demonstrated substantial associations of household independent and joint activity patterns, household/individual characteristics and travel behavior. Such relationships are described by the total, direct, and indirect effects furnished by the model system. As expected, there is a trade-off between joint maintenance and independent maintenance, and more importantly, the effect direction from joint maintenance to independent maintenance is more significant than otherwise. One interesting finding is that there is a complementary relationship between joint discretionary and joint maintenance. As proposed by Kuppam and Pendyala (2001), the trade-offs and complementarities among activities are useful in explaining the trip chaining behavior of commuters.

In addition, this study is of practical values in that it can be used to evaluate the impacts of certain policy actions. For instance, teleworking males will increase out-of-home joint activities with their wives, but decrease out-of-home independent maintenance, in comparison with other males who work outside home. We also find that if travel time is shortened, then at least a part of those timesavings will be spent on joint activities. These insights could help improve activity-based travel modeling for accurate travel forecasting and reliable transportation policy analysis.

However, the approach has several limitations. One obvious limitation was the small sample size, which might lead to three consequences: 1) making the original sample especially susceptible to the effects of outliers before they were removed (Mokhtarian and Meenakshisundaram, 1999); 2) reducing the precision with which effects could be estimated, and precluded more sophisticated models of interaction; and 3) precluding more extensive investigation into activity patterns. For instance, only relationships among out-of-home weekday activities are taken into account. In-home and weekend activities are also important and might show different patterns of interactions. Another limitation is that, all activities are aggregated into separate broad types across all five weekdays to investigate time allocation, which might show different patterns on each individual day.

In response to the limitations noted above, future studies should: 1) cover in-home as well as out-of-home activities, if the sample size permits; 2) compare independent and joint activity participation patterns between weekdays and weekend day; and 3) extend involved persons of joint activities to the whole household, not just adult household heads, in so doing, to get more realistic model estimates.

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Chapter 4 Modeling Day-to-Day Dynamics in Individuals' Activity Time Use Considering Intra-household Interactions

4.1 Introduction

Variability analysis, which investigates the extent to which our activity-travel decisions give rise to consistent patterns, has been a topic of interest in travel behavior research for quite some time (Pas, 1987). The total variability in daily behavior is decomposed into two constituent parts: interpersonal and intrapersonal variability, which are either systematic or random (Koppelman and Pas, 1984; Pas, 1987; Pas and Sundar, 1995). Interpersonal variability refers to "the differences in the activity-travel behavior among different individuals on the same day or over different days"; intrapersonal variability refers to "the differences in the activity-travel behavior demonstrated by the same individual over time."

There are many advantages to conducting variability analysis, as identified by previous studies (Bhat et al., 2004; Bhat et al., 2005; Hirsh et al., 1986; Jones and Clark, 1988; Kitamura, 1988; Koppelman and Pas, 1984; Muthyalagari et al., 2001; Pas, 1986). First, from a policy viewpoint, variability analysis may better reflect changes in behavioral patterns of individuals in response to policy actions (e.g., workweek compression) than a single-day study (Bhat et al., 2004; Bhat et al., 2005; Hirsh et al., 1986) by capturing association among activities across days of the week. Second, variability studies aiming to investigate how activity/trips are organized over a multi-day period within the constraints of individuals, households, and the urban area, can help address the most fundamental issue of travel behavior analysis -Why do individuals make trips the way they do?(Kitamura, 1988). Last, it is found that in travel demand analysis, if a multi-day sample is employed, as opposed to a one-day sample, not only is survey cost reduced, but also estimators are more efficient (Pas, 1986; Pas, 1987) and less biased (Bhat et al., 2005; Bhat et al., 2004; Hirsh et al., 1986).

Within the activity context, most behavioral studies have employed a single-day or a pooled sample for the analysis of activity-travel patterns (Bhat et al., 2005). One implicit assumption is that activity decisions are uniform and independent from one day to the next (Bhat et al., 2005), which obviously does not reflect real activity-travel decision patterns. For instance, unlike work, which is conducted regularly, other activities such as grocery shopping or recreation tend to have a longer cycle for participation (Bhat et al., 2005). Even for workers, their daily activity patterns might be different in that they have relatively less time available for other types of activities (e.g., discretionary) on working days compared to non-working days. It can be anticipated that their time allocation decision on working days and on non-working days are not independent. As indicated by Yamamoto and Kitamura (1999), in such cases, transportation policies effective on weekdays would affect time use on weekend days, while time use on weekend days may affect how a worker responds to the policies on weekdays.

The main reason for prior single-day studies is the lack of long-duration activity-travel surveys, which is necessary for analyzing variability. As identified by Schlich and Axhausen (2003), to collect surveys over a long period, there are two difficulties facing interviewed persons: 1) high response burden; and 2) ignoring short trips with increasing duration of the survey. Even when data are available for multiple days, the day-to-day variations in time allocations of household members are captured, at best without taking into account intra-household interactions. This is attributable to the fact that, in the past, many activity-travel surveys have failed to collect information on involved persons. This has been especially true for the large-scale, trip-based surveys that underpin urban travel demand models around the world. Although this appears to be changing, even if collected, such information, without proper validation, may not be reliable due to recall errors by sampled individuals(Kang and Scott, 2008).

The objective of this study is to better understand variability in time allocation by household members over a multi-day period. To the best of our knowledge, this study extends earlier work in two key aspects: first, intra-household interactions are uniquely incorporated into individuals' time allocation patterns; second, day-to-day variations in such decisions are examined. The increased analytical difficulty due to such extension will assist in a better understanding and characterization of travel behavior dynamics by shedding light on the planning of activities over the course of one week. The data set used for this study is collected from the 2003 CHASE (Computerized Household Activity Scheduling Elicitor) survey that was conducted in Toronto, Ontario (Doherty and Miller, 2000).

The reminder of this chapter consists of four sections, starting with a review of the literature where variability in activity-travel behavior has been examined, with a focus on their empirical findings and limitations of past studies. Based upon this, some descriptive analyses are conducted to explore interpersonal variability and intrapersonal variability associated with household activity time allocation. Next, a suite of models are developed in this study to describe daily time allocation to out-of-home non-work activities over the course of a week. They comprise of seven day-specific models (one for each day of the week) and one pooled weekly model for comparison purposes. This chapter concludes with a summary of our findings and directions for future research.

4.2 Literature Review

Multi-day analysis has largely focused on the day-to-day variability in travel behavior of individuals, with only a few studies pertaining to activities (Bhat et al., 2004). Within the travel behavior context, variability studies mostly examine certain attributes of travel decisions (e.g., trip rates, purpose, modes, timing and duration, pattern classification) (Hanson and Huff, 1982; Hanson and Huff, 1988; Jones and Clark, 1988; Kitamura, 1988; Pas, 1988; Pas and Koppelman, 1986; Schlich et al., 2004; Schlich and Axhausen, 2003). Among them, the Uppsala, Sweden studies (Hanson and Huff, 1982; Hanson and Huff, 1986;

Hanson and Huff, 1988; Huff and Hanson, 1990; Huff and Hanson, 1986), using the 35-day household travel survey, and the Reading, England studies (Pas, 1988; Pas, 1987; Pas, 1986; Pas and Koppelman, 1986), using the 7-day activity survey represent the most widely known efforts to examine intrapersonal variability in travel behavior. Their empirical findings questioned the ability of travel demand models based on a single day sample to produce good forecasts and/or accurately evaluate policy actions (Buliung and Roorda, 2006).

Within the activity context, most behavioral studies have employed a single-day or a pooled sample for analysis of activity patterns (Bhat et al., 2005). One implicit assumption is that activity decisions are uniform and independent from one day to the next (Bhat et al., 2005), which obviously does not reflect real activity-travel decision patterns. There are a limited number of studies focusing on variations of activities (Habib and Miller, 2008; Ma and Goulias, 1997; Susilo and Kitamura, 2005). For example, Ma and Goulias (1997), using data from the Puget Sound Transportation Panel, suggested that activity and travel patterns should be examined at different time scales in order to separate behavioral variation arising from daily, weekly, monthly, and yearly habits. Susilo and Kitamura (2005) examined variability in individuals' action space using the 6-week travel diary data from Karlsruhe and Halle, Germany. Their results showed that the variability of action space is influenced by obligatory activities on weekdays and discretionary activities on weekend days. In particular, the spread of activity locations demonstrated by workers and students is relatively stable within weekdays. Habib and Miller (2008) modeled within-day and day-to-day dynamics in activity-travel behavior with an emphasis on activity program generation by incorporating variables of "total working hours" and "previous day's total executed activities". It is identified that Monday, Thursday and Sunday are different from the other days in terms of "goodness of fit to the observed data, number of statistically significant variables, and the effects of travel time in activity-travel planning".

Within the context of time allocation patterns, Bhat and Misra (1999) and Yamamoto and Kitamura (1999) examined the allocation of discretionary time between weekdays and weekends while accommodating the trade-offs and relationship between in-home and out-of-home discretionary activities. Their studies have offered empirical evidence that associations exist in time allocation between working days and non-working days. In particular, Yamamoto and Kitamura (1999) indicated that about 70% of the sample workers tended to spend more time on out-of-home discretionary activities on working days and more time on in-home discretionary activities on non-working days, contrary to popular belief.

The above studies as well as other activity-based studies are typically conducted at the individual level (Ettema et al., 1993; Kitamura et al., 1996; Kraan, 1996). However, in many instances, household members interact before they decide about activities they perform and the time involved (Zhang et al., 2003). One example would be that a couple has to coordinate vehicle sharing if there is only one available in the household. Recognition of the importance of interactions among household members has recently produced a growing body of research (Bradley and Vovsha, 2005; Gliebe and Koppelman, 2002; Golob and McNally, 1997; Goulias and Hensen, 2006; Kang and Scott, 2008; Kato and Matsumoto, 2006; Lu and Pas, 1999; Scott and Kanaroglou, 2002; Srinivasan and Bhat, 2006). Therefore, previous studies using the individual as the behavioral unit of analysis, are limited because of their inability to explicitly accommodate inter-individual interactions in activity-travel behavior (Bhat and Koppelman, 1999).

To overcome such limitation, Yamamoto and Kitamura (1999) attempted to account for the effects in intra-household interactions by applying household size and children as explanatory variables. They both have highly significant coefficient estimates in the model. However, as suggested by Bhat et al. (2004), the effect of interaction between household members cannot be fully captured by simple measures such as marital status, spouse's employment characteristics, and household structure. Conversely, individual activity behavior should be examined within the broader context of household. Golob and McNally (1997) developed a structural equations model to analyze interactions in time allocation to out-of-home activities and travel between male and female heads in a household. Zhang et al. (2003) developed the g-Logit household time use model to incorporate group decision-making mechanisms. Other research efforts that have been undertaken to capture inter-individual interaction effects (Fujii et al., 1999; Gliebe and Koppelman, 2002; Golob and McNally, 1997; Jones et al., 1983; Lu and Pas, 1999; Sener and Bhat, 2007; van Wissen, 1989). Their empirical findings provide extensive insights concerning interactions in time allocations among individuals in a household as well as among various activity-travel categories for each individual.

It is clear from the literature that there exists an urgent need to examine day-to-day variations of activity time-use patterns while incorporating interactions among household members. Specifically, the purpose of this study is to better understand variability in individuals' time allocation over a multi-day period within a household context.

4.3 Data Source

The 2003 (Computerized Household Activity Scheduling Elicitor) data set is used for the variability analysis (Doherty and Miller, 2000). This dataset has been used by Habib and Miller (2008) to examine day-to-day dynamics in activity program generation, representing a typical weekly cycle of individuals' activity-travel behavior.

To explicitly capture intra-household interactions, joint activities are differentiated from independent activities by using the GIS toolkit we developed (Kang and Scott, 2008). In the past, many activity-travel surveys have failed to collect information on involved persons. This has been especially true for the large-scale, trip-based surveys that underpin urban travel demand models around the world. Although this appears to be changing, even if collected, such information, without proper validation, may not be reliable due to recall errors by sampled individuals. Under such circumstances, using traditional restrictive criteria (i.e., same timing, specific activity type/travel mode) will likely underestimate the number of joint episodes. Therefore, this toolkit is developed to ensure that all occurrences of joint episodes are accounted for, in spite of such inconsistent reporting.

The core of this toolkit is a set of flexible criteria (i.e., same location, same aggregated activity type/mode, and flexible time, a 10-minute difference in the starting time and a 10-minute difference in the ending time) for identifying joint activities from a data set (Kang and Scott, 2008). The flowchart shown in Figure 2.6 illustrates how joint episodes are identified by the GIS toolkit (See Appendix A).

After joint activities are identified by using the GIS toolkit, we limit our analysis to married or unmarried male and female couples, while removing households of unrelated individuals (e.g., college roommates) (Golob and McNally, 1997). It might be equally important to investigate other companion types of interpersonal interactions, such as between adults and children (Kato and Matsumoto, 2006; Sener and Bhat, 2007), or among non-household members (Srinivasan and Bhat, 2008). However, such a differentiation (i.e., according to companion type) requires a larger sample size to allow for more parameters to be estimated. After controlling for the quality of respondent records and location data, the final sample used in this study consists of 96 households and 192 adults for each day of the week. Furthermore, our analysis focuses on out-of-home episodes, because of the fact that an out-of-home episode requires travel, while an in-home episode does not (Jones and Clark, 1988). The substitution relationship between in-home and out-of-home activities has been reported by past studies (Bhat and Misra, 1999; Jones et al., 1983; Kitamura et al., 1996; Kraan, 1996; Yamamoto and Kitamura, 1999). Finally, all out-of-home non-work activities are classified into four categories in terms of companion type (i.e., independent vs. Joint) and activity attributes: independent maintenance, independent discretionary, joint maintenance and joint discretionary (see Table 4.1 for detailed descriptions), and time allocation to each category was calculated by summing the time spent by the same individual on every single episode of the same type on each day.

Table 4.1 Definitions of variables

Variables	**Definition**
Activity duration	
Independent maintenance	Total daily time spent on out-of-home independent maintenance activity per person
Joint maintenance	Total daily time spent on out-of-home joint maintenance activity by both household heads
Independent discretionary	Total daily time spent on out-of-home independent discretionary activity per person
Joint discretionary	Total daily time spent on out-of-home joint discretionary activity by two household heads
Household characteristics	
Home ownership	1 = households owning a house; 0 = otherwise
Children present	1 = households having 1or more kids (6 years old or younger); 0 = otherwise
Car ownership	1 = households with at least 1 car per adult; 0 = otherwise
Individual characteristics	
Age <35	1 = people younger than 35 years; 0 = otherwise
Age >65	1 = people older than 65 years; 0 = otherwise
Teleworking	1 = people working at home; 0 = otherwise
Low income (<=10,000)	1 = people with an income of 10,000 or lower, 0 = otherwise
High income (>=70,000)	1 = people with an income of 70,000 or higher, 0 = otherwise
Education level (BS or higher)	1 = people with a Bachelor's or higher degree, 0 = otherwise

Note: maintenance includes household obligations, drop-off/pick-up, shopping and services, and other needs; discretionary includes meals, services, active recreation, social and other

4.4 Descriptive Analysis

This section of the chapter discusses results of our descriptive analysis. Figure 4.1 presents the average daily time spent on each type of out-of-home non-work activity undertaken by each person across days of the week. The figure shows that household members, on an average, allocate more time to out-of-home (non-work) activities on weekend days compared to weekdays. This is attributable to the constraints associated with work which occur mostly on weekdays, as opposed to on weekends (Schlich and Axhausen, 2003). However, one interesting thing to note is that the increase of daily time investment in joint activities is substantially higher than in independent activities from weekdays to weekends. In particular, time spent on joint discretionary activity on weekends is twice as long as that on weekdays. This can be explained by the fact that household members are separated from each other for most weekdays because of work, thereby reducing the time allocated to joint activity participation (Srinivasan and Bhat, 2008).

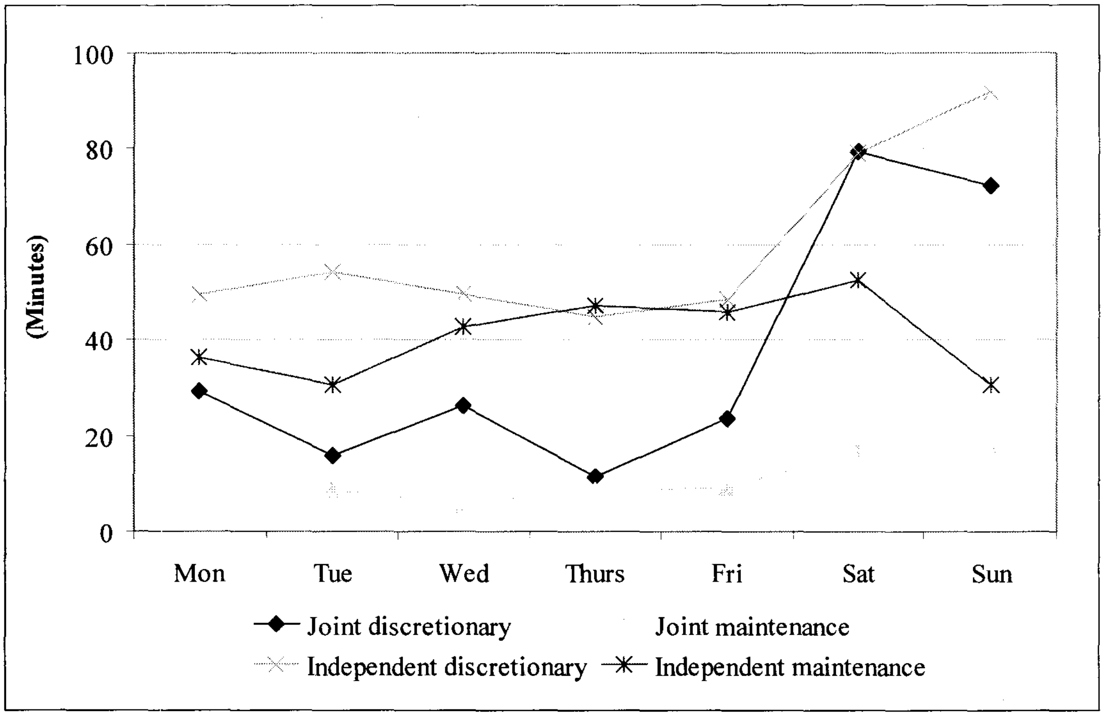

Figure 4.1 Average activity time allocations by each person across days of the week

Next, total variability is calculated by the total sum of squares (TSS) and its two components - interpersonal variability and intrapersonal variability. They are represented by the between-person sum of squares (BPSS) and the within-person sum of squares (WPSS) respectively (Pas, 1987):

$$TSS = \sum_{j} \sum_{i \in M_j} \sum_{k} (t_{ijk} - \bar{t})^2$$

$$BPSS = K \sum_{j} \sum_{i \in M_j} (t_{ijk} - \bar{t})^2$$

$$WPSS = \sum_{j} \sum_{i \in M_j} \sum_{k} (t_{ijk} - \bar{t}_{ij})^2$$

where

t_{ijk} is the total duration of a given activity type by person i of household j on day k,

$\bar{t}$ is the overall sample average duration of a given activity type per person per day,

$\bar{t}_{ij}$ is the average duration of a given activity type made per day by person i of household j,

M_j is the set of all persons in household j,

K is the number of days in the observation period.

To probe further into the nature of day-to-day dynamics, the variability is investigated at three time scales: across one week, within weekdays, and within weekends. Proportions of intrapersonal and interpersonal variability out of the total variability are presented in Table 4.2. Several interesting observations are made from these statistics. First, at different time scales, intrapersonal variability across one week is higher than that within weekdays, which is then followed by within weekends. Such an observation applies to all types of out-of-home non-work activities. Second, compared to independent activities, intrapersonal variability in joint activities (i.e., joint maintenance and joint discretionary) is larger at all three time scales investigated here. In other words, joint activities (irrespective of activity type) are more variable over time, compared to independent activities. For instance, for joint maintenance, intrapersonal variability accounts for 82% of the total variability across one week, 78% within weekdays and 48% within weekend days only, which accounts for 71%, 55% and 39% respectively in the case of independent maintenance.

Table 4.2 Intrapersonal and interpersonal variability in activity time use

Time scale	Variability	Independent maintenance	Independent discretionary	Joint maintenance	Joint discretionary
Across one week	Intrapersonal	71%	66%	82%	76%
	Interpersonal	29%	34%	18%	24%
Weekdays	Intrapersonal	55%	58%	78%	71%
	Interpersonal	45%	42%	22%	29%
Weekend days	Intrapersonal	39%	22%	47%	35%
	Interpersonal	61%	78%	53%	65%

4.5 Empirical Models

4.5.1 Structural Equations Modeling (SEM)

SEM is chosen for modeling individuals' time allocation because it can capture complex relationships among socio-demographics, and activity participation simultaneously (Lu and Pas, 1999). Golob has pioneered the application of this methodology in the transportation field, and together with his colleagues has used it to address a wide variety of transportation problems (Golob, 1990; Golob and McNally, 1997). Recently, application of structural equation models (SEM) has been proposed as a means to investigate interpersonal interactions (Fujii et al., 1999; Golob, 2000; Golob and McNally, 1997; Lu and Pas, 1999; Meka et al., 2002; Simma and Axhausen, 2001).

Following the matrix notation of Lu and Pas (1999), an SEM for observed variables can be defined as:

$$y = By + \Gamma x + \zeta$$

where

B is $p \times p$ matrix of coefficients, representing the direct effects of endogenous variables on other endogenous variables,

Γ is $p \times q$ matrix of coefficients, representing the direct effects of exogenous variables on endogenous variables,

y is a $p \times 1$ vector of endogenous variables,

x is a $q \times 1$ vector of exogenous variables,

ζ is a $p \times 1$ vector of errors in the equations, with the standard assumption that ζ is uncorrelated with x.

In addition to B and Γ, $\Phi(q \times q)$ is the covariance matrix of x and $\Psi(p \times p)$ is the covariance matrix of ζ. As structural equations models are estimated using covariance (structure) analysis. The fundamental idea of estimating the structural equations modeling is that Σ, the population covariance matrix of observed variables x and y, can be expressed by the unknown parameters (B, Γ, Φ, Ψ). Then, such parameters are estimated through minimizing the discrepancies between the observed covariance matrix and the population covariance matrix Σ (Lu and Pas, 1999).

To explore day-to-day variations of activity time allocation, a SEM is developed for each day of the week. For all seven day-specific models, endogenous variables are the same, which are daily time allocation to out-of-home non-work activities (i.e., independent maintenance, independent discretionary, joint maintenance and joint discretionary) (see Table 4.1). A worker's total daily work duration is fixed in the short term, and hence is incorporated into the model as a constraint imposed upon time allocation to other activity types (Yamamoto and Kitamura, 1999). For comparison purposes, a weekly model is developed, considering the whole week as the planning period. Different from the day-specific models, endogenous variables of the weekly model are the week-long time allocation to out-of-home non-work activities, and a worker's work duration represents the sum of working time over a week. In all the above models, exogenous variables include household characteristics and individual characteristics, the choice of which is guided by previous literature and also constrained by data availability. The final set of exogenous variables is listed in Table 4.1.

4.5.2 Interpretations of SEM

The models are presented in Table 4.3. Given the relatively small data set compared to the larger number of parameters to be estimated, the coefficients reported here are considered statistically significant if their corresponding two-tailed t-statistics satisfy the 90% confidence interval, ($t \geq 1.64$) (Habib and Miller, 2008). The goodness of fit measures, Akaike information criterion (AIC), Browne-Cudeck (BCC), Bayes information criterion (BIC) and consistent AIC (CAIC) are used for comparing models to each other, and not for judging the merit of a single model. In comparison to AIC, BCC, CAIC and BIC impose greater penalty for model complexity, and the order of penalty imposed by each measure is as follows: BIC > CAIC > BCC, which reflect a combination of good fit to the data and parsimony. According to these measures, all the day-specific models are better than the pooled weekly model. This reflects the inability of the weekly model to capture day-to-day variations of time-use patterns compared to day-specific models (Habib and Miller, 2008).

Table 4.3 Structural equation model estimates for daily out-of-home time allocation (total effects)

Variables		**Day of week**	**Independent maintenance**	**Independent discretionary**	**Joint maintenance**	**Joint discretionary**
Activity duration	*Work*	Mon	-0.298	-0.273	-	-0.144
		Tue	-0.218	-0.226	-0.206	-0.175
		Wed	-0.234	-0.232	-0.244	-0.252
		Thu	-0.45	-0.288	-	-
		Fri	-0.386	-0.167	-0.107	-0.162
		Sat	-	-	-	-0.142
		Sun	-	-0.13	-	-
		Whole week	-0.391	-0.28	-	-
	Independent maintenance	Tue	-	-	-0.026	-0.164
		Fri	-	0.05	0.277	-
		Sat	-	-	-0.16	-0.156
	Independent discretionary	Wed	-	-	-0.199	-
	Joint maintenance	Mon	-	-0.152	-	-
		Fri	-	0.181	-	-
	Joint discretionary	Tue	-	-	0.157	-
		Wed	-	-0.143	0.196	-
		Thu	-	-	0.141	-
		Sun	-0.15	-	-	-
		Whole week	-	-	0.128	-
Household characteristics	*Children present (≤ 6 years)*	Mon	-	0.026	-0.173	-
		Wed	-	0.018	-0.025	-0.127
		Sun	-	-	-0.142	-
		Whole week	-	-	-0.179	-0.166
	Car ownership (with at	Tue	-	-	0.028	0.177

	least one car per adult)	Wed	-	-	0.28	-
		Fri	0.137	0.007	0.038	-
		Sat	-	-	-	0.313
		Whole week	0.124	-	0.161	-
	Home ownership	Tue	-	-	-0.035	-0.222
		Wed	-	0.021	-0.158	-0.144
		Thu	-	-	-0.039	-0.274
		Fri	-	-0.027	-0.148	-
Individual characteristics	*Teleworking*	Mon	-	-0.031	0.205	0.239
		Thu	-	-	0.02	0.142
		Sat	0.246	-	-0.039	-0.038
		Sun	0.196	-	-	-
		Whole week	-	-	0.015	0.119
	Low income	Tue	0.172	-	-0.004	-0.028
		Wed	-	0.028	-0.038	-0.196
		Sat	-	-	0.13	-
	High income	Mon	-0.136	-	-	-
		Sun	-	-	0.127	-
		Whole week	-0.139	-	-	-
	Age < 35 years	Sat	-	0.139	-	-
		Sun	-	0.205	-	-
	Age > 65 years	Mon	-	-0.035	0.228	-
		Thu	-0.163	-	-	-
		Whole week	-0.165	-0.139	-	-
	Education level (BS or higher)	Fri	-	-0.027	-0.151	-
		Sun	-0.021	-	-	0.139

Day-to-day variability in individuals' time-use patterns within the context of household is discussed as follows:

First, the constraining impact of work on other activity types is uniform across days of the week, which appears to be stronger on weekdays compared to weekends. This is represented through: 1) on weekdays, work significantly reduces time allocation to all other four activity types, but only reduces duration of joint discretionary on Saturday and independent discretionary on Sunday; and 2) the scale of such negative impact is larger on weekdays than on weekends. In other words, an increasing amount of work duration leads to a larger reduction of time allocation to other activities on weekdays than on weekends. This is in line with the finding that individuals tend to spend more time on out-of-home (non-work) activities on weekends compared to weekdays (see Figure 4.1). Furthermore, by differentiating joint activities from independent activities, more insights can be gained concerning householders' time allocation patterns. For instance, one interesting finding is that there is a positive relationship between joint discretionary and joint maintenance. In other words, household members are more inclined to take part in joint maintenance activities outside the home may also exhibit a greater tendency to participate in recreation together. This could be attributable to the trip chaining effect (2001).

Second, impacts of household and individual-level socio-demographics on time allocated to different activity types (i.e., independent vs. joint activities) have also been investigated over the course of one week. The following household-level variables are identified to significantly impact time allocations of household members: children present, car ownership, and home ownership in this chapter. Specifically, couples with presence of children (6 years old or younger) are more inclined to undertake out-of-home independent maintenance activities, but are less likely to undertake out-of-home joint maintenance and joint discretionary activities across days of the week. This is attributable to constraints imposed by young children upon couples (Scanzoni and Szinovaez, 1980). Our finding is consistent with many prior studies (Bhat and Misra, 1999; Chandraskharan and Goulias, 1999; Gliebe and Koppelman, 2002; Jones et al., 1983; Kostyniuk and Kitamura, 1983; Scanzoni and Szinovaez, 1980; Townsend, 1987). Another significant variable on activity time allocation is household car ownership. Our empirical results indicate that family members with higher car availability (i.e., at least one car per adult) tend to undertake more joint activities together across weekdays and weekends. That is to say, owning more cars does not reduce joint activities as expected (e.g., because of the removal of mobility constraints), but encourages participation in such activities. This is attributable to some benefits associated with participation in joint activities (e.g., lowering fuel costs and companionship). Comparatively, it is much easier to understand the positive effect of car ownership on participation of out-of-home independent activities. Our empirical results have also illustrated the influence of home ownership on time allocation patterns, which has long been unexplored by many prior studies. Specifically, in comparison with renters, couples owning a house are less likely to undertake joint activities, which might be due to some extra responsibilities associated with home ownership, such as mowing the lawn.

Compared to household-level variables, estimated coefficients of individual characteristics are more variable from day to day, especially between weekdays and weekends. This is consistent with our descriptive results that intrapersonal variability across days of the week is higher than that within weekdays and within weekends. The most noticeable difference may be in the impact of teleworking on activity time allocation. Teleworking has been a very interesting Travel Demand Management measure, which is proposed to reduce peak period demand (Salomon, 1998). In this chapter, the association of teleworking and joint activity participation is found to be positive for weekdays, but negative for weekends. The converse is observed for independent activities. The potential reason for this is that participation in joint activities needs coordination between people, and teleworking people have a more flexible work schedule on weekdays than people who work outside home. However, on weekend days, teleworkers are more likely to undertake independent activities compared to joint activities. It implies that teleworking might help reduce travel demand through car sharing by household members, which does not hold true for all days of the week. Age and income are two common variables which have been found to influence time allocation patterns by many studies (Habib and Miller, 2008; Srinivasan and Bhat, 2008; Yamamoto and Kitamura, 1999). Differently, in this study, these two variables are incorporated as dummy variables, which are expected to provide more insights into the process of time allocation. Specifically, compared to the middle-aged (35-65) (as the reference group), younger people (<35 years) tend to spend more time on independent activities on weekends, while the retired (>65 years) are likely to spend less time on independent activities, but more time on joint activities on weekdays. This could be attributable to the fewer constraints imposed by work activity on retired people than on younger people. Similarly, impacts of income level on time allocations vary between weekdays and weekends. Specifically, on weekdays, compared to the middle class, people with higher income tend to spend less time on independent activities, while lower income individuals are more inclined to independent activities, but less to joint activities. However, on weekends, both groups of people (i.e., lower income level and higher income level) appear to allocate more time to joint activities than the middle class. Education level is another variable, which shows different impacts on joint time allocation between weekdays and weekends.

4.6 Discussion and Conclusion

Most prior activity studies have employed a one-day or a pooled sample for analyzing activity-travel patterns, which are typically conducted at the individual level. They assume that activity decisions are uniform from one day to the next and individuals are independent from each other. This obviously does not reflect real activity-travel decision patterns. In this context, the objective of our study is to better understand variations of individuals' time allocation over a multi-day period while accommodating intra-household interactions. Specifically, sum of squares (Pas, 1987), which has been largely used in the travel behavior context, is initially adopted to measure interpersonal and intrapersonal variability in activity time allocation. Then, a suite of models are developed in this study to investigate time allocation to out-of-home non-work activities over a week, which comprises seven day-specific models (one for each day of the week) and one pooled weekly model for comparison purposes.

Results derived from the descriptive analysis and model estimations provide evidence of day-to-day variability in activity time-use patterns. Specifically, time allocated to out-of-home non-work activities is more variable between weekdays and weekends than within weekdays and within weekends. Such variability is clearly captured by day-specific models, but not by the pooled weekly model. Hence caution must be exercised in drawing conclusions from prior aggregated activity studies. Furthermore, by differentiating joint activities from independent activities, extensive insights can be gained concerning householders' time allocation patterns. For instance, compared to independent activities, joint activities are more variable over time.

The empirical results are of practical values in that they provide more insights concerning travel demand management measures. For instance, teleworking has been proposed to reduce peak period demand (Salomon, 1998). In this study, we find that teleworkers are more likely to take part in out-of-home joint activities with their family members on weekdays, but not on weekends. This means that teleworking might help reduce travel demand through sharing cars between household members, which does not hold true all days of one week. Additionally, our empirical results suggest that family members with higher car availability (i.e., at least one car per adult) tend to undertake more joint activities together over the course of one week. That is to say, owning more cars does not reduce joint activities as expected (e.g., because of the removal of mobility constraints), but encourages participation in such activities instead. This might be attributable to some benefits associated with undertaking joint activities (e.g., lowering fuel costs and companionship).

This study can be extended along two directions: First, if a larger data set (e.g., the American Time Use Survey) was used, it would be possible to estimate more parameters. Hence, we could investigate variability in the substituting effect of in-home and out-of-home activities, and/or to decompose joint activities into more categories (e.g., according to the companion type: with children, with spouse, or both), in so doing, to get more comprehensive investigation; Second, a data set with longer surveying period (e.g., Mobidrive, which is a six-week travel diary) might provide more insights into dynamics of weekly activity time-use patterns.

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Chapter 5 An Investigation of Planning Priority of Joint Activities in the Household Activity Scheduling Process

5.1 Introduction

The activity-based approach in travel demand modeling implies a shift in focus from trips to activities assuming that most travel is not an end in itself but a means to bridge activities that are separated in time and space. Within the activity-based approach context, observed patterns are the result of an underlying activity scheduling process by which individuals decide which activities to conduct, where, when, for how long, sometimes with whom, and the transport mode used to undertake their activities, given a variety of constraints (e.g., situational, institutional, household, spatial and temporal constraints) (Arentze and Timmermans, 2004). A series of modeling efforts have long been devoted to understanding the scheduling process, mainly using the utility maximization (UM) approach, originating from the economic theory of consumer choice (Bowman, 1998; Jones et al., 1983; Kawakami and Isobe, 1990; Recker et al., 1986). These models, however, are criticized for their assumption of a one-step planning process, which has been found to be a dynamic scheduling process consisting of preplanning, revision, and impulsive decisions (Doherty et al., 2001; Doherty and Axhausen, 1999; Doherty and Miller, 2000; Ruiz and Roorda, 2008).

Over the past decade, transportation researchers have been interested in investigating dynamic process of activity scheduling, which might be helpful to improve the effectiveness of congestion management and intelligent transportation systems (Lee and McNally, 2006). Growing recognition of the dynamic scheduling process has resulted in another approach to modeling activity scheduling. Such approach suggests that key attributes of activities (e.g., type, duration, location, mode, etc.) are sequentially planned and executed (Arentze and Timmermans, 2004; Cullen and Godson, 1975; Ettema et al., 1993; Gärling et al., 1994; Gärling et al., 1998; Kitamura, 1983; Kitamura, 1997; Lee and McNally, 2006; Lee and McNally, 2003; Miller and Roorda, 2003; Vand der Hoorn, 1983). Within this line of research, Cullen and Godson (1975), through collecting empirical data, validated the hypothesis that certain activities in one's daily schedule tend to act as "pegs" around which other more flexible activities are arranged, while spontaneous activities are inserted at the last. Based on Cullen and Godson's theory, Lee and McNally (Lee and McNally, 2006; 2003) further investigated attributes (e.g., activity type, duration, etc.) of those "pegs". In particular, they find that certain activity types, such as work and social activities usually fill daily schedules before any other events, while in-home activities and recreation/entertainment activities tend to be implemented impulsively when free time is available. Additionally, activities with shorter duration are often spontaneously inserted in a schedule already anchored by activities with longer duration. Their studies also indicate that female respondents tend to be more structured in terms of planning activities relative to males. In addition, Travel time required to reach an activity is another deciding factor of the scheduling horizon for the activity - with more distant stops being planned earlier than closer locations (Lee and McNally, 2006; 2003).

Developing models of the activity-scheduling process has met with considerable challenges. One of the overriding themes is that in previous modeling practices, a fixed order of sequencing by activity type is often assumed (Mohammadian and Doherty, 2006). The SCHEDULER (Gärling et al., 1989), SMASH (Ettema et al., 1993), ALBATROSS (Arentze and Timmermans, 2004), and TASHA (Miller and Roorda, 2003) assume that household members sequentially schedule their activity-travel decisions in a priority based (Doherty, 2000; Ettema et al., 1993). Specifically, one common assumption is that mandatory activities (i.e., skeleton or peg) are planned before discretionary activities and out-of-home activities are planned before in-home activities (Arentze and Timmermans, 2004). However, the validity of such assumptions has been recently questioned (Doherty, 2006; Mohammadian and Doherty, 2006; Roorda and Miller, 2005). As suggested by Mohammadian and Doherty (Mohammadian and Doherty, 2006) the planning priority of certain activities is clearly not always fixed. For instance, some discretionary activities (e.g., watching a hockey) may share some of the same characteristics of more "mandatory" activities, which tend to be pre-planned without much flexibility. Furthermore, even within the same activity type – work, teleworkers might have more flexible schedules for working than typical workers. In this case, putting work in a skeleton schedule is probably inappropriate. Therefore, they suggest that a fixed order of sequencing by activity type should be avoided in order to make the model more sensitive to capture individual responses to emerging policy action scenarios (Mohammadian and Doherty, 2006).

Another challenge is that intra-household interactions have been incorporated into the activity-based scheduling model, at best, by exogenously assuming the priority of planning joint activities relatively to independent activities. It has been widely recognized that household members interact in many ways to coordinate their activity-travel decisions (Bradley and Vovsha, 2005; Carrasco and Miller, 2006; Gliebe and Koppelman, 2002; Gliebe and Koppelman, 2005; Goulias and Hensen, 2006; Hollander and Prashker, 2006; Kang and Scott, 2008; Miller and Roorda, 2003; Scott and Kanaroglou, 2002; Srinivasan and Athuru, 2005; Srinivasan and Bhat, 2008; Srinivasan and Bhat, 2006). During the scheduling process, examples of household interaction include generation of joint activity episodes, household vehicle sharing and coordination necessary for taking care of children (Miller and Roorda, 2003). In TASHA, the order of planning priority is statically assumed as: work-business episodes>primary work episodes>all other work episodes>school episodes>joint other episodes>joint shopping episodes>individual other episodes>individual shopping episodes (Miller and Roorda, 2003). Similarly, Vovsha et al. (2003) assumed that individual mandatory commitments take precedence over all other joint and individual activities; joint nonmandatory activities come next in the hierarchy, while individual nonmandatory activity has the lowest priority.

Finally, the scheduling pattern of joint activities across different participants has remained largely unexplored. In TASHA, to allow for the interaction that occurs within a household, joint activities are assumed to be generated simultaneously for different household members (Miller and Roorda, 2003). Such implementation may not reflect the real scheduling process, since individual characteristics have been found to impact their scheduling process (Lee and McNally, 2003; Mohammadian and Doherty, 2005). For instance, for certain activity types, such as joint shopping, it might be pre-planned by the wife, but impulsively undertaken by the husband.

Our study is designed to addresses the challenges discussed above by investigating the planning priority of joint activities. Specifically, a bivariate probit model is developed to examine the planning priority of joint activities for female and male household heads respectively. In our analysis, joint activities are classified according to the order in which they are planned (impulsive or pre-planned) by female and male household heads, respectively. A variety of explanatory variables are used including activity attributes and household/individual characteristics. Ideally, this study will help support the development of scheduling models, which move beyond static priority assumptions for determining sequencing of joint activities.

The reminder of this chapter consists of four sections. First, the data set used for our study is introduced, followed by data processing and some exploratory analysis of planning priority. Then a bivarite probit model is developed, followed by interpretations of our empirical results. This chapter concludes with a discussion of our findings and limitations.

5.2 Data Source

The 2003 CHASE (Computerized Household Activity Scheduling Elicitor) survey used for this study was conducted in Toronto, Ontario. A detailed description of the design and conduct of this survey can be found in Doherty and Miller (2000).

The CHASE data is ideally suited for our analysis especially because the question of "when planned" is collected over a 7-day horizon. Specifically, when adding activities to their schedule in CHASE, users were often asked "when did you originally plan this activity?", with the following five options: 1) just before the activity (<5 minutes); 2) prior to the activity on the same day; 3) before the day of the activity; 4) I didn't really give it much thought – it happened as part of a regular routine; and 5) I cannot recall. Results of this prompt are primarily used to determine the priority when activities were planned. Although "just before the activity" and "prior to the activity on the same day" are both scheduled and performed within the same day, the difference is that spur of the moment events are relatively spontaneous and within day events might have a minimal level of planning involved (Lee and McNally, 2006). Therefore, responses to option 1 are classified as "impulsive", and those to options 2 – 4 are classified as "pre-planned", while activities without clearly specifying planning priority were excluded. The data set contains 240 households, including 474 adults. In total, these sampled adults undertook a total of 28,680 activity episodes during one week, each of which is associated with all types of attributes (e.g., location, type, duration, etc.).

To ensure that all occurrences of joint episodes are accounted for, the Space-Time Coincidence Analyst GIS toolkit we developed was applied to the CHASE data set (Kang and Scott, 2008) (see Appendix A). The toolkit was designed to overcome issues such as inconsistent reporting about starting and ending times, different perceptions of activity purposes by household members, along with other ambiguities involved in a survey data set. Eventually, 8,055 joint activities are identified from the original survey. The following extensive data screenings are performed. First, similar to Golob and McNally (1997), we limit our analysis to married and unmarried male and female couples. Additionally, our analysis focuses on out-of-home episodes only, because of the fact that an out-of-home episode requires travel, while in-home episode does not (Jones and Clarke, 1988). Furthermore, we limit our consideration of jointness to maintenance and discretionary activities only, because these types are most likely to be pursued jointly (Gliebe and Koppelman, 2002; Kang and Scott, 2008).

Before conducting model estimations, exploratory analysis is performed, from which it is found that 75.4% of joint activities are pre-planned by female household heads, while 71.1% by male household heads. This verifies the finding of Lee and McNally (2003), and Mohammadian and Doherty (2005) that female household heads are more likely to pre-plan activities than their husbands, although in their studies, joint and independent activities are not differentiated from each other. Furthermore, over a quarter of joint activities are undertaken impulsively, instead of being planned in advance, which questioned the validity of assumptions in most scheduling models as discussed above. Then, to investigate the relationship of female and male's decision making, the chi-square test of independence is conducted, and a value of 121.9 ($p = 0$) indicates that there is a statistically significant relationship between female and male household heads when planning joint activities. This will be further explored by the modeling effort.

5.3 Methodology

The bivariate probit model (BVP) is useful for analyzing interdependence between two binary endogenous variables. With the observation subscripts suppressed, the BVP model (Greene, 2003) is:

$y_1^* = \beta_1 x_1 + \varepsilon_1$, $y_1 = 1$ if $y_1^* > 0$, 0 otherwise

$y_2^* = \beta_2 x_2 + \varepsilon_2$, $y_2 = 1$ if $y_2^* > 0$, 0 otherwise

$[\varepsilon_1, \varepsilon_2] \sim$ bivariate normal (BVN) $[0,0,1,\xi]$

where

$[y_1^*, y_2^*]$ = latent variables,

$[y_1, y_2]$ = the observed outcomes,

$[\beta_1, \beta_2]$ = vectors of coefficients to be estimated,

$[x_1, x_2]$ = vectors of explanatory variables influencing the outcomes,

$[\varepsilon_1, \varepsilon_2]$ = random error terms, and ξ is correlation coefficient between the two error terms.

The BVP model is considered an extension of the multinomial logit (MNL) model in which the Independence of Irrelevant Alternatives (IIA) assumption of the MNL model is relaxed. However, the random error terms ε_1 and ε_2 are assumed to be normally distributed. In comparison with two individual probit equations, the BVP model has the advantage of taking into account the correlation between two decision making process, in our case, the planning priority of female and male household heads. In our model, each decision maker (i.e., husband and wife), is faced with two alternatives when planning joint activities, which are pre-planned and impulsive. Explanatory variables include three groups: activity-related attributes (duration, starting time, travel time, spatial flexibility[13] and temporal flexibility[14]), individual characteristics (age, job duration, employment status, education level, income and cell phone usage) and household characteristics (income, house status, household size, presence of kids and auto ownership), the choice of which is guided by previous literature (Mohammadian and Doherty, 2005; Mohammadian and Doherty, 2006; Ruiz and Roorda, 2008) and also constrained by data availability. The final set of variables are listed in Table 5.1.

13 Spatial flexibility was measured as the number of locations considered for the activity, where a value of 0 indicates that it is fixed to one location, and a value of 1 indicates a greater level of flexibility (i.e., more locations considered for it).

14 Temporal flexibility ranged from 0 to 1, where values close to 0 indicate activities fixed in time, whereas values close to 1 are very flexible in time. The value was calculated by first dividing the average observed duration by the duration of the time window that the activity could occur in.

Table 5.1 Descriptive statistics of the independent variables used in the model

Variables	Definition	Categorical variables (Percentages)	Continuous variables mean	s.d.
Dependent Variables				
Female pre-planning	1 = female household head who pre-plan the out-of-home joint activity; 0 = otherwise	75.38		
Male pre-planning	1 = male household head who pre-plan the out-of-home joint activity; 0 = otherwise	71.08		
Independent Variables				
Household attributes				
Number of children	Number of children (<=6 years old) in household		0.60	0.99
Number of adults	Number of adults in household		2.35	0.61
Couple, two-worker	1 = households in which two household heads work; 0 = otherwise	84.72		
Household dwell type	1 = house is detached or semi-detached; 0 = otherwise	88.89		
Living in Toronto	1 = household in Toronto; 0 = otherwise (other cities in GTA)	18.06		
Individual attributes				
Male age	Male age		50.31	12.69
Female age	Female age		47.22	13.73
Female with high income	1 = female household head's income higher than 75,000 (inclusive); 0 = otherwise	11.11		
Female cell-phone user	1 = female household head who is a cell-hone user; 0 = otherwise	27.78		
Male working duration (>=5 years)	1 = male household head who has worked	41.67		

	longer than 5 years (inclusive); 0 = otherwise			
Activity-related attributes				
Duration of activity (>=2 hours)	1 = total duration of the scheduled activity longer than 2 hours (inclusive); 0 = otherwise	33.23		
Starting in peak period	1 = activity starting in peak period (7:00-8:59 or 16:00-17:59); 0 otherwise	30.46		
Auto travel time to the activity	Total auto travel time to the activity (observed, in minutes)		13.76	18.95
Temporal flexibility	1= activity which is very flexible in time; 0 otherwise	48.62		

5.4 Results

Our empirical results of the bivariate probit model are presented in Table 5.2. With the dependent variables of female and male's planning alternative (i.e., impulsive vs. pre-planning), the bivariate probit model estimates two binary regressions, each with a distinct set of coefficient estimates. The correlation coefficient is significant $(0.8757, p = 0)$, indicating that a bivariate probit model rather than two univariate probit is more appropriate, and the planning priority of female and male undertaking joint activities is positively related and significant. This is also consistent with our chi-square test of independence as discussed above. The BVP model performs well as indicated by high classification accuracy (76.31%) and a large likelihood ratio, ρ2 (0.2353). In the following sections, the effect of variables by variable category is discussed. Variables used in the model represent household and individual attributes, activity-related attributes. In each binary regression, a positive coefficient suggests that a higher value of an explanatory variable is associated with that the individual tends to pre-plan the joint activity. For example, in the binary regression of female planning, a positive coefficient for travel time suggests that activities requiring longer time of traveling are more likely to be pre-planned by a household head. In the two sub-models, the estimated association between the planning priority and each variable is generally in the expected direction. All reported parameter estimates are statistically significant at the 90% level or higher.

Table 5.2 Bivariate probit results of female and male planning priority

	Female planning priority			Male planning priority		
	Coefficients	*t*-statistics	*P*	Coefficients	*t*-statistics	*P*
Constant	-0.9682	-1.5890	0.1121	-0.4011	-0.6660	0.5056
Household attributes						
Number of children	0.3288	2.2460	0.0247	0.2834	2.0110	0.0444
Number of adults	-0.3036	-2.0920	0.0364	-0.4688	-3.0910	0.0020
Couple, two-worker	0.9585	3.9180	0.0001	0.8204	3.2860	0.0010
Household dwell type	-1.0475	-3.5640	0.0004	-	-	-
Living in Toronto	-	-	-	0.4809	1.9360	0.0529
Individual attributes						
Male age	-	-	-	0.0205	2.4890	0.0128
Female age	0.0386	4.9410	0.0000	-	-	-
Female cell-phone user	-	-	-	0.4315	1.6660	0.0957
Female with high income	-0.7575	-1.9150	0.0555	-	-	-
Male working duration (≥5 years)	-	-	-	-0.6008	-3.1890	0.0014
Activity-related attributes						
Duration of activity (≥2 hours)	0.7251	2.9960	0.0027	0.6801	2.9760	0.0029
Starting in peak period	-	-	-	0.3912	2.0160	0.0438
Auto travel time to the activity	0.0322	3.3570	0.0008	0.0281	2.6590	0.0078
Temporal flexibility	-	-	-	-0.3321	-1.8370	0.0663
Disturbance correlation – $\rho(1,2)$		0.8757	16.848	0		
Sample size		325				
Overall classification accuracy		0.7631				
Log-likelihood function and likelihood ratio						
L*(0), log-likelihood function at constants		-318.9754				
L*(β), log-likelihood function at convergence		-243.9184				
ρ^2, likelihood ratio index		0.2353				

(-) Variable not included in model

Starting with the household socio-demographics, the effects of household characteristics on the planning priority of individuals are generally consistent with earlier studies (Lee and McNally, 2006; Mohammadian and Doherty, 2005; Mohammadian and Doherty, 2006; Ruiz and Roorda, 2008), although, in their studies, joint activities are differentiated from independent activities. As expected, the total number of children in a household has a positive coefficient in the preplanning alternative for both the female and the male household head. This is attributable to the extra pressure of pre-planning activities associated with childcare (Mohammadian and Doherty, 2005). Another influential factor of the planning priority is the number of adults living in the same household. It indicates that couples living with other adults are less likely to pre-plan joint activities compared to couples without living with other adults. This is due to relatively fewer childcare constraints imposed upon those couples, since other adults (e.g., grandparents) in their household might be available to help with babysitting (Bhat and Gossen, 2004).

Concerning the employment status of the household, if both household heads are employed, they are more likely to pre-plan activities than other households. The notion of Mohammadian and Doherty (Mohammadian and Doherty, 2005) that employment tends to lead to more planning in order to fit in other activities appears to hold. Another interesting finding is that household dwell type has an important impact on planning joint activities. Specifically, female detached unit dwellers are unlikely to pre-plan joint activities compared to other dwellers in non-detached units, such as apartments. In addition, male household heads living in urban areas (i.e., Toronto) are more likely to pre-plan joint activities than others living in suburban. Although there is evidence indicating that the type of household dwelling and residence location might affect activity patterns (Bhat and Gossen, 2004), their impacts on scheduling priority have remained largely unexplored in past studies, not to mention within the context of joint activities. Individual-related explanatory variables are also explored in our study. As expected, the older people and cell phone users tend to plan joint activities in advance, which are consistent with findings by Mohammadian and Doherty (Mohammadian and Doherty, 2005). Furthermore, females with higher income and males who work over than 5 years are less likely to pre-plan joint activities.

Turning attention to activity-related attributes, activity duration has a positive coefficient in the pre-planning alternative, which suggests that activities with longer durations usually tend to be pre-planned in advance. This conforms to the notion that longer activities require more scheduling efforts to make time for or to avoid conflicts with other activities, while shorter activities tend to be spontaneous (Lee and McNally, 2006; Mohammadian and Doherty, 2005; Ruiz and Roorda, 2008). Additionally, activities that have a start time in the peak period (7:00 – 8:59 or 16:00 – 17:59) are more likely to be pre-planned by male household head, which might be attributable to issues such as traffic congestion. Travel time has the expected positive effect in pre-planned joint activities for both female and male household heads. This suggests that activities with longer travel time require more advanced planning and are less likely to be planned impulsively. This is as expected given the costs involved in traveling longer distance in terms of time, money, and mode availability (Lee and McNally, 2006; Mohammadian and Doherty, 2005). The temporal flexibility indicator is negatively associated with the male's pre-planning. In other words, if the activity is more temporally flexible, it tends to be planned closer to execution time, whereas activities that are more temporally fixed are planned much earlier. This is also consistent with findings by Mohammadian and Doherty (Mohammadian and Doherty, 2005).

Perhaps of great interest in this modeling effort are some of the variables that are not significant. In particular, it appears logical that joint shopping activities are assumed to be more flexible and thus of lesser priority by many operational models such as TASHA (Miller and Roorda, 2003). However, activity type variables such as joint maintenance and discretionary are not significant in the model. Doherty (Doherty, 2006) argues for abandoning the use of traditional activity types (work, school, shopping, etc.) in the activity-based modeling. Instead, he suggests that focus should be on the more salient attributes of activities that serve to more directly explain how they are scheduled, modified and subsequently executed, leading to travel, such as the spatial and temporal flexibility of activities. In our study, the temporal flexibility is found to have a significant impact on the male's pre-planning decision as described above. Another promising variable that did not enter significantly in the model is day of week (e.g., weekday vs. weekend), because joint activity participation has found to be substantially different on weekdays and weekends Srinivasan and Bhat (Srinivasan and Bhat, 2008).

Table 5.3 presents the predicted and observed frequency of the planning priority by female and male household heads. Columns are the predictions made by males and rows indicate the predictions made by females. The higher value along the diagonal represent cases in which females and males made the same responses. This confirms the chi-square test of independence that female and male household heads are highly associated when planning joint activities.

Table 5.3 Predicted and observed frequency of female and male planning priority

Female planning priority	Male planning priority		
	Impulsive	Pre-planned	Total
Impulsive	39	1	40
	(62)	(18)	(80)
Pre-planned	7	278	285
	(32)	(213)	(245)
Total	46	279	325
	(94)	(231)	(325)

Note: () represent observed frequency of female and male planning priority

5.5 Discussion and Conclusion

There is some general recognition that incorporating interpersonal interactions in travel-demand modeling is important for realistic forecasts and policy evaluation (Srinivasan and Bhat, 2008). The growing recognition of intra-household interactions has led to a rapid expansion of research and development of technologies that can incorporate such interactions into activity-based scheduling models. Within this context, our study attempts to investigate the scheduling priority for female and male household heads who participate in out-of-home, non-work joint activities together. This study also examines effects of individual characteristics, household socio-demographics and activity-related characteristics on the planning priority. Our analysis is necessary first step in informing the development of a behaviorally sound activity-scheduling model that truly reflects the planning priority of joint activities in each individual scheduling process.

In this study, all the out-of-home, non-work joint activities undertaken by couples are classified according to the order in which female and male household heads planned (pre-planning or impulsive). Instead of using two separate univariate probit models, the bivarite probit model is employed to investigate the relationship between female and male priority of scheduling joint activities. A wide variety of different types of variables contributed significantly to the model, linking basic activity-related attributes, household and personal socio-demographics. With respect to the significance and sign of each explanatory variable, most of the effects were as expected and were consistent with priori empirical results. The model has a good fit given the capability of the data set and model. Overall, interpretation of this first attempt to explicitly investigate the planning priority for household heads undertaking joint activities led to several interesting insights.

First, not all joint activities are planned in advance, although this has been widely assumed by most scheduling models which accommodate intra-household interactions. Specifically, it is found that over a quarter of joint activities are planned closer to execution time by their participants - female and male household heads. Second, female and male household heads show different priority patterns when planning joint activities. That is, in general, females tend to pre-plan joint activities in comparison with their husband. Furthermore, gender effects are represented as different impacts of same explanatory variables on the females and male. For instance, the dwelling type seems to play a more important role in dictating female's planning priority, so does the residence location on male's planning priority. Additionally, some activity attributes (e.g., temporal flexibility) have a larger impact on male household heads, compared to female household heads. Overall, to develop a behaviorally sound model for activity scheduling, our study highlights the important need to validate static assumptions regarding priority of joint activities and suggests taking into account the disparity across different participants.

As with most research efforts of this type, limitations apply to this study. Despite the best efforts, our empirical results may be sensitive to model specification and choice of explanatory variables. Also, besides the generation of joint activity episodes, household interactions also occur during the household vehicle sharing or the coordination necessary for care of the children within the context of activity scheduling. Additional research is warranted in order to develop a model for activity scheduling which moves beyond static priority assumptions for determining sequencing of activities.

5.6 References

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Chapter 6 Conclusions

The recognition of intra-household interactions in activity-travel modeling is very important for improving the accuracy and reliability of forecasts and evaluating impacts of policy actions. In contrast to this importance of accommodating interpersonal dependencies in activity modeling, much of the research efforts have focused on modeling individuals' activity patterns independent of activity –travel choices of other household members.

The research presented in this dissertation makes important contributions to activity-based time use and travel behavior research by uniquely and directly incorporating intra-household interactions. Technically, the developed GIS toolkit is helpful to reduce the costs (both time and money) associated with the processing of large activity-travel datasets. Empirically, impacts of household interactions in shaping activity patterns of household members are examined. Thus, the research findings presented in this dissertation will form the basis toward the development and implementation of an improved activity-based time use and travel behavior model. The contributions of this research are discussed with more details in the following section.

6.1 Contributions to Activity-based Modeling

Contributions of this dissertation made to activity-based modeling are discussed under two main headings: (1) identification of intra-household interactions and (2) incorporation of intra-household interactions.

6.1.1 Identification of Intra-household Interactions

This research moves beyond past activity-based studies by developing the first household-based GIS toolkit for automatically identifying and visualizing (3D) joint activity/travel episodes. This makes it possible to uniquely and directly incorporate intra-household interactions into studies of activity/travel behavior.

In the past, many activity/travel surveys have failed to collect information on involved persons. This has been especially true for the large-scale, trip-based surveys that underpin urban travel demand models around the world. Although this appears to be changing, even if collected, such information, without proper validation, may not be reliable due to recall errors by sampled individuals. Furthermore, in existing household-based activity/travel surveys, respondents tend to report about starting and ending times inconsistently, or activity purposes differently. Under such circumstances, using traditional restrictive criteria (i.e., same timing, specific activity type/travel mode) will likely underestimate the number of joint episodes. Therefore, the core of this toolkit is developing a set of flexible criteria to ensure that all occurrences of joint episodes are accounted, in spite of such inconsistent reporting.

Specifically, this toolkit includes two tools, namely, the Space-Time Coincidence Analyst tool and the Space-Time Path Visualizer tool, which are complimentary, but independent. In other words, the two tools, collectively, support functions including the identification of joint episodes, the representation of space-time paths, and spatio-temporal relationships of these paths in 3D, or they can be used independently, depending on the user's purpose. In addition, the toolkit is very user-friendly and very powerful to reduce the costs (both time and money) associated with processing large household-based, activity/travel data sets to identify joint episodes. Furthermore, because of its flexible design, the toolkit can be applied to any household-based, activity/travel data set.

The toolkit also allows for a comparison of important attributes of joint and independent activities between restrictive and flexible criteria. Those key attributes include frequency, timing, duration and composition of activity purposes. Our empirical study, which applies the toolkit to the 2003 CHASE data set, suggests that considerable variation exists in the number of joint activity/travel episodes identified using different classification criteria. Specifically, when using restrictive criteria (i.e., same timing, specific activity type/travel mode), only 2,265 joint activity/travel episodes are identified compared to 8,791 when using more flexible criteria. In turn, the results show that certain key attributes for independent and joint activity/travel episodes (i.e., frequency per household, starting time, ending time and duration) also vary under the different classification criteria. Also, the composition of joint episodes is compared when using different criteria, which has direct implications for how to improve designs of future activity/travel surveys.

6.1.2 Incorporation of Intra-household Interactions

Once joint activity episodes are identified, the task remains to understand activity patterns by the way they incorporate elements of joint participation (i.e., intra-household interactions). The dataset used for this research is the 2003 CHASE (Computerized Household Activity Scheduling Elicitor) survey collected in the Greater Toronto Area (Doherty and Miller, 2000). As described above, joint episodes are identified by using the GIS toolkit (Kang and Scott, 2008), which is designed to overcome issues such as inconsistent reporting about starting and ending times, different perceptions of activity purposes by household members, along with other ambiguities involved in a survey data set. Eventually, 8,055 joint activities are identified when using flexible criteria, compared to 1,795 when using restrictive criteria. The following extensive data screenings were performed.

Guided Golob and McNally (1997), the analysis is limited to married and unmarried male and female couples in the same household, within which more interactions are expected than unrelated individuals. Additionally, our analysis focuses on out-of-home episodes only, mainly because of the fact that an out-of-home episode requires travel, while in-home episode does not (Jones and Clarke, 1988). Furthermore, as reported by Gliebe and Koppelman (2002) and Kang and Scott (2008), the types of activities most likely to be pursued jointly are maintenance and leisure activities. Thus, the emphasis of this research is just placed on joint maintenance and joint discretionary activities.

The research presented in Chapter 3, 4 and 5 makes three general contributions by incorporating intra-household interactions into several aspects of activity-based modeling.

First, interactions among household members are explicitly incorporated to deepen our understanding about household time allocation patterns in Chapter 3. Specifically, a structural equations model of out-of-home weekday time allocation is developed and applied to analyze activity time allocation patterns by household heads. The model is unique in its simultaneous representation of intra-household interactions, intra-person interactions and their socio-demographic factors. Overall, the model demonstrates substantial associations of household independent and joint activity patterns, household/individual socio-economic characteristics and travel behavior. All the empirical results appear very plausible and consistent with past literature (Golob and McNally, 1997; Kuppam and Pendyala, 2001; Lu and Pas, 1999).

As expected, there is a trade-off between joint maintenance and independent maintenance, but a complementary relationship between joint maintenance and joint discretionary. This is very useful in explaining the trip chaining behavior of commuters Kuppam and Pendyala (2001). Also, this research confirms and clarifies motivations and constraints of joint activity participation in the context of household-based modeling. And the empirical results are of practical values in that it can be used to evaluate the impacts of certain policy actions. For instance, teleworking males tend to participate in more out-of-home joint activities with their wives, but decrease their own independent maintenance, in comparison with other males who work outside home. These insights could help improve the performance of activity-based travel modeling in evaluating transportation policy actions, which also highlight the important of need to accommodate intra-household and intra-person interactions in activity-travel behavior analysis.

Another uniqueness of this research is that the impact of choosing different criteria for identifying joint activities on the model performance and research findings has also been examined. Almost all previous studies of household activity patterns have used restrictive criteria for such identification. The empirical results suggest that choosing different classification criteria for identifying joint activities has an impact on the model performance and research findings. Specifically, the performance of the flexible model is better than that of the restrictive model, although regression effects of the flexible model appear consistent with estimates of the restrictive model in terms of signs and scale. Furthermore, the flexible model is able to capture more relationships than the restrictive model.

Second, another relatively undeveloped facet of household activity-travel modeling is addressed in Chapter 4, namely, interpersonal and intrapersonal variability in household activity time allocation patterns. Interpersonal variability refers to "the differences in the activity-travel behavior among different individuals on the same day or over different days"; intrapersonal variability refers to "the differences in the activity-travel behavior demonstrated by the same individual over time" (Pas, 1987). Most activity-based studies have employed a single-day dataset by assuming that activity patterns are uniform and independent from one day to the next (Bhat et al., 2005). This differs, however, from the reality of people allocating time into different activities.

In this chapter, variability is investigated through descriptive analysis and structural equations modeling, which, to our knowledge, represents the initial effort in the activity-based context. First, the average duration of all five out-of-home activity types per person per day over the course of one week is compared within one week. Then sum of squares, which has been used to measure variability in travel behavior, is uniquely introduced into activity-based modeling for quantifying interpersonal and intrapersonal variability (Pas, 1987). Finally, an SEM is estimated on each day of the week. For all the seven models, endogenous variables are the same, which are out-of-home durations of independent maintenance, independent discretionary, joint maintenance and joint discretionary. The exogenous variables used in this study include household attributes, individual attributes, and work duration. The choice of variables is guided by previous literature and it is also constrained by data availability.

Results derived from the descriptive analysis and model estimation results bring about the following conclusions. First, interpersonal and intrapersonal variability are all but negligible within one week. Second, compared to the day-to-day variability, the variability between weekdays and weekends is much bigger. Overall, the empirical results highlight the importance of accounting for variability in household time allocation, which will help improve activity-based modeling especially in three following aspects: (1) it captures association among activities across the week, demonstrated by people when selecting their weekly activity patterns; (2) it avoids the bias inherent in daily activity models; and (3) it is more sensitive to policies affecting the weekly patterns of activities (Hirsh et al., 1986).

Finally, Chapter 5 endeavors to explore the activity scheduling process, by which individuals decide which activities to conduct, where, when, for how long, sometimes with whom, and the transport mode used undertake their activities. Household members interact in many ways to coordinate their schedules (Arentze and Timmermans, 2004). However, in most operational models, intra-household interactions have been incorporated, at best, by making static assumptions. For instance, in TASHA (Miller and Roorda, 2003), it is assumed that joint activities tend to pre-planed. Furthermore, the priority of planning joint activities is assumed to be same for all involved household members. This study addresses a relatively undeveloped facet of household activity-travel systems, investigating whether such assumptions hold true through empirical studies.

In this particular research, all the out-of-home, non-work joint activities undertaken by couples are classified according to the order in which female and male household heads planned (pre-planning or impulsive). In the analysis, bivariate probit models are estimated respectively for two main household decision-making units: husband and wife. A wide variety of different types of variables contributed significantly to the model, linking basic activity-related attributes, household and personal socio-demographics. Overall, the empirical results from this study highlight the important need to validate static assumptions regarding priority of joint activities before application and also to accommodate disparity across individual participants when developing activity-based microsimulation models. Interpretation of these results led to several interesting insights. First, not all joint activities are planned in advance, although it has been widely assumed by most scheduling models. Furthermore, the activity type itself may not suffice to explain fully how they are planned. To enhance the behavioral validity of activity scheduling models, certain explanatory variables such as activity duration, estimated travel time, age, gender, employment status, and household locations could be incorporated to guide or validate their static assumptions. Second, different scheduling patterns are observed between participants of joint activities - female and male household heads, which means that they should be treated separately in activity scheduling models.

Overall, the research presented in this dissertation makes important contributions to activity-based time use and travel behavior research. Technically, the developed GIS toolkit is helpful to reduce the costs (both time and money) associated with the processing of large activity-travel datasets. Theoretically, the empirical results presented in these studies will form the basis toward the development and implementation of an improved activity-based time use and travel behavior model.

6.2 Directions for Future Research

The dual technical and theoretical emphasis of the dissertation has led to several possible directions for future research. These include (1) enhancement of GIS toolkit developed for identifying intra-household interactions, and (2) comprehensively incorporation of intra-household interactions into activity-based modeling.

First, the GIS toolkit could be extended to identify joint participation in activity/travel episodes by more than two household members. Such an extension could be conducted by the researcher through follow-ups. For instance, if the researcher is interested in joint episodes undertaken by three family members, a simple query (i.e., JTOT_01=1 and TOT_02=1) can be built easily and quickly either in ArcGIS or Microsoft Access.

Second, the data set used for exploring intra-household interactions in this dissertation is limited in terms of the sample size. The CHASE data set contains 240 households, including 474 adults, who undertook a total of 28,680 activity episodes during one week, from which only 8,055 joint activities are identified for 96 households. If a larger dataset is available, more extensive investigation into activity patterns would be allowed. This would also improve the performance of activity-based modeling. Specifically, the current research could be extended in two key aspects. First, with a larger dataset, more sophisticated models (i.e., estimating more dependent variables) would be developed and estimated in order to gain more insights into activity-based modeling. Specifically, it would be interesting to investigate in-home activity patterns, their dynamics over time and planning priority during the household scheduling process. For instance, a substitution effect between in-home and out-of-home activities might be expected, which will provide additional insight on household activity patterns. Also, if the sample size permits, joint activities can be differentiated into more categories, according to the type of the involved person (e.g., children, spouse, or parents), in so doing, to get more realistic model estimates. Second, a larger sample size could reduce the effects of outliers and improve the precision of model estimations (Mokhtarian and Meenakshisundaram, 1999).

Third, household interactions also occur during the household vehicle sharing or the coordination necessary for care of the children, besides the generation of joint activity episodes. Additional research into such areas is warranted in order to develop a behaviorally sound model for activity scheduling which moves beyond static priority assumptions for determining sequencing of activities.

6.3 References

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Appendix A: Components of the Space-Time Coincidence Analyst tool

The flowchart shown in Figure 2.6 illustrates how joint episodes are identified. From the original survey, activity events (points) and travel events (lines) are created in the 2D plane. Then for each type of file, the Intersect method is used to identify episodes, for which any two household members share the same location. Following this, the other two criteria (timing and type/mode) are implemented by queries discussed in the above section. Once queries are posed, newly created variables are attached to the original survey data, indicating whether each episode is undertaken by two householders together or independently, by using both flexible and restrictive criteria, respectively[15]. Therefore, our toolkit can be used to compare results arising from these two criteria. Also, for joint activities, the exact joint starting times and joint ending times are calculated and appended to the output files for any two household members.

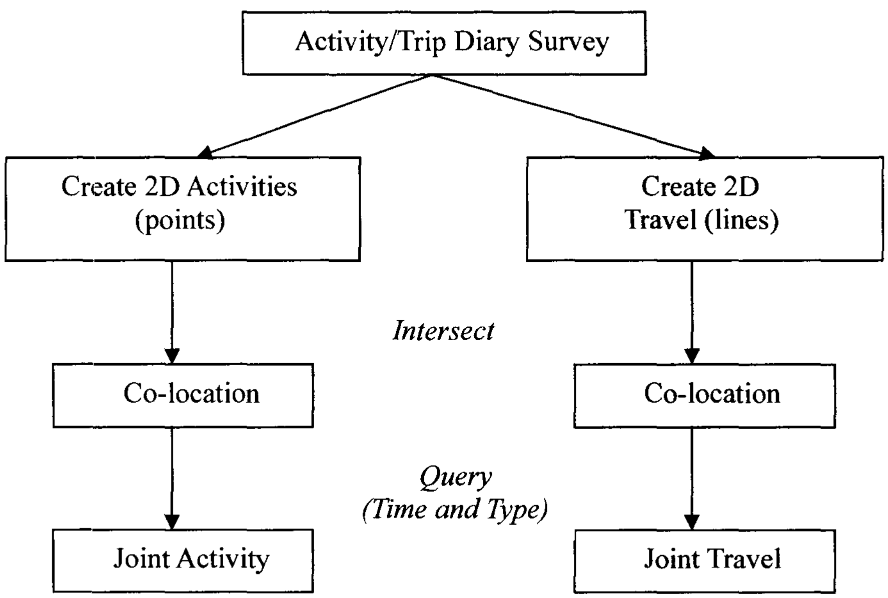


Figure 2.6 A flowchart for identifying joint episodes

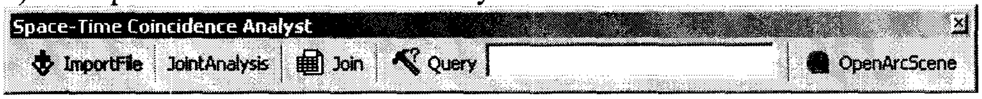
15 For example, if there are three members within one household (persons 0, 1 and 2), three new variables are added, which are JTOT_01 (indicating whether person 0 and 1 are undertaking activities together), JTOT_02 (indicating whether person 0 and 2 are undertaking activities together) and JTOT_12 (indicating whether person 1 and 2 are undertaking activities together). At the same time, three other fields (JSTOT_01, JSTOT_02, and JSTOT_12) are created, which indicate whether an episode is joint or independent, but based on restrictive criteria instead. Similarly, all the above indicators are generated for traveling.

Figure 2.7 displays the interfaces of the Space-Time Coincidence Analyst toolkit. This toolkit recognizes joint activities/travel undertaken by any two household members, and further outputting desired results to certain files specified by the user. This toolkit is comprised of five components, which are: 1) ImportFile; 2) JointAnalysis; 3) Join; 4) Query; and 5), OpenArcScene, building a connection to the ArcScene window (Figure 2.7a).

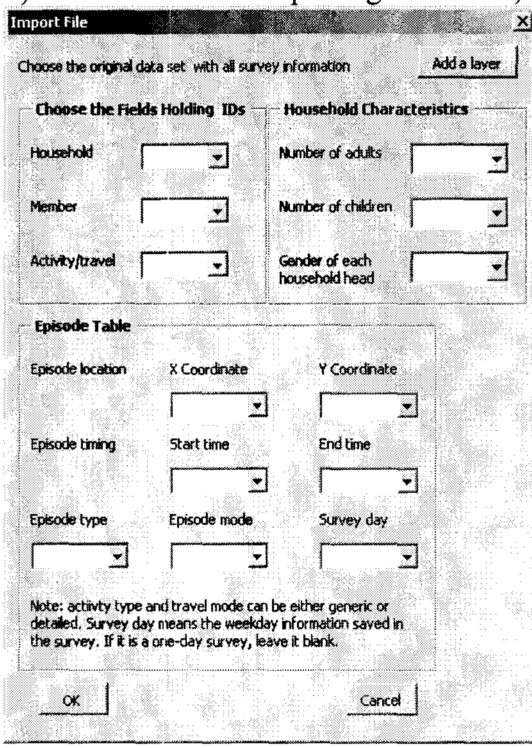
ImportFile serves to prepare data for analysis, which asks the user to locate required fields of a survey file (see Figure 2.7b). Such a design reflects the flexibility of our tool, which can be applied to most surveys, as long as necessary information is input. Since our toolkit is designed for the exploration of intra-household interactions, the following basic information is required: 1) IDs, which include Household ID, Member ID and Activity/Travel ID; 2) household characteristics, collecting information such as the number of adults and children in each household as well as the gender of each household head; and 3) episode table, which stores some basic information about each episode (activity/travel) recorded in the survey data set. This includes the location (xy coordinates), timing (starting/ending times), episode type, travel mode and the time frame of the survey. As long as the above information is identified, the analyst tool can be used for various household surveys (i.e., one-day or multiple-day) from different regions, except for those focusing only on one household member. The reason for this is that the tool is designed specifically to explore intra-household interactions.

Once the survey file is imported, the next step is to classify joint activities and travel (see Figure 2.7c). Through this step, newly created variables are attached to the original survey data, indicating whether each episode is undertaken by two householders together or independently, by using both flexible and restrictive criteria, respectively. Therefore, our toolkit can be used to compare results arising from these two sets of criteria. Also, for joint activities, the exact joint time period is calculated and appended to the output files for any two household members. The next step called "Join" appends these indicators to the original survey data set (see Figure 2.7d). To facilitate exploration, a "Query" interface is also designed to meet particular requirements by the user, who may want to focus on certain household types (i.e., single with children, couple without children, and couple with children). Once a certain type is chosen, the "Next" button brings the user to the corresponding user-friendly interface (see Figure 2.7e). For each query, the output is saved as a database file into a directory designated by the user.

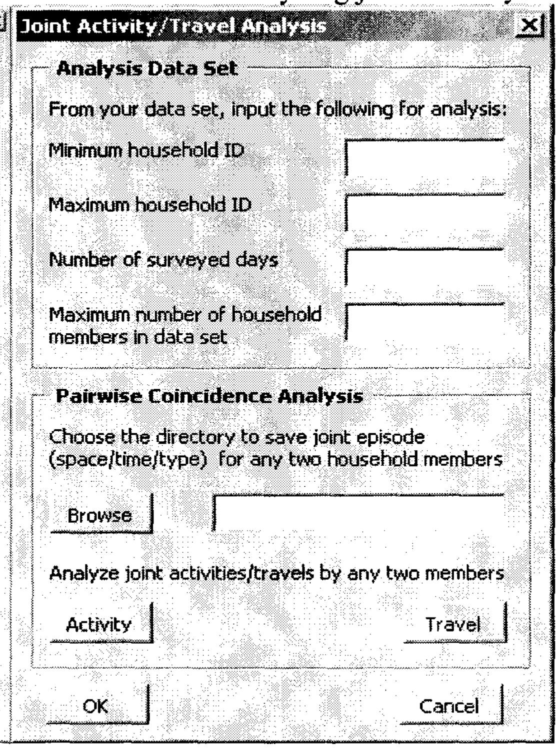
a) The Space-Time Coincidence Analyst toolbar



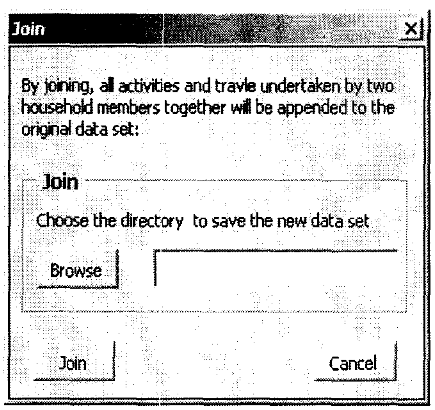
b) The interface for importing files



c) The interface for analyzing joint activity/travel



d) The join interface



e) The interface for query (household type: single with children; couple with children; couple without children)

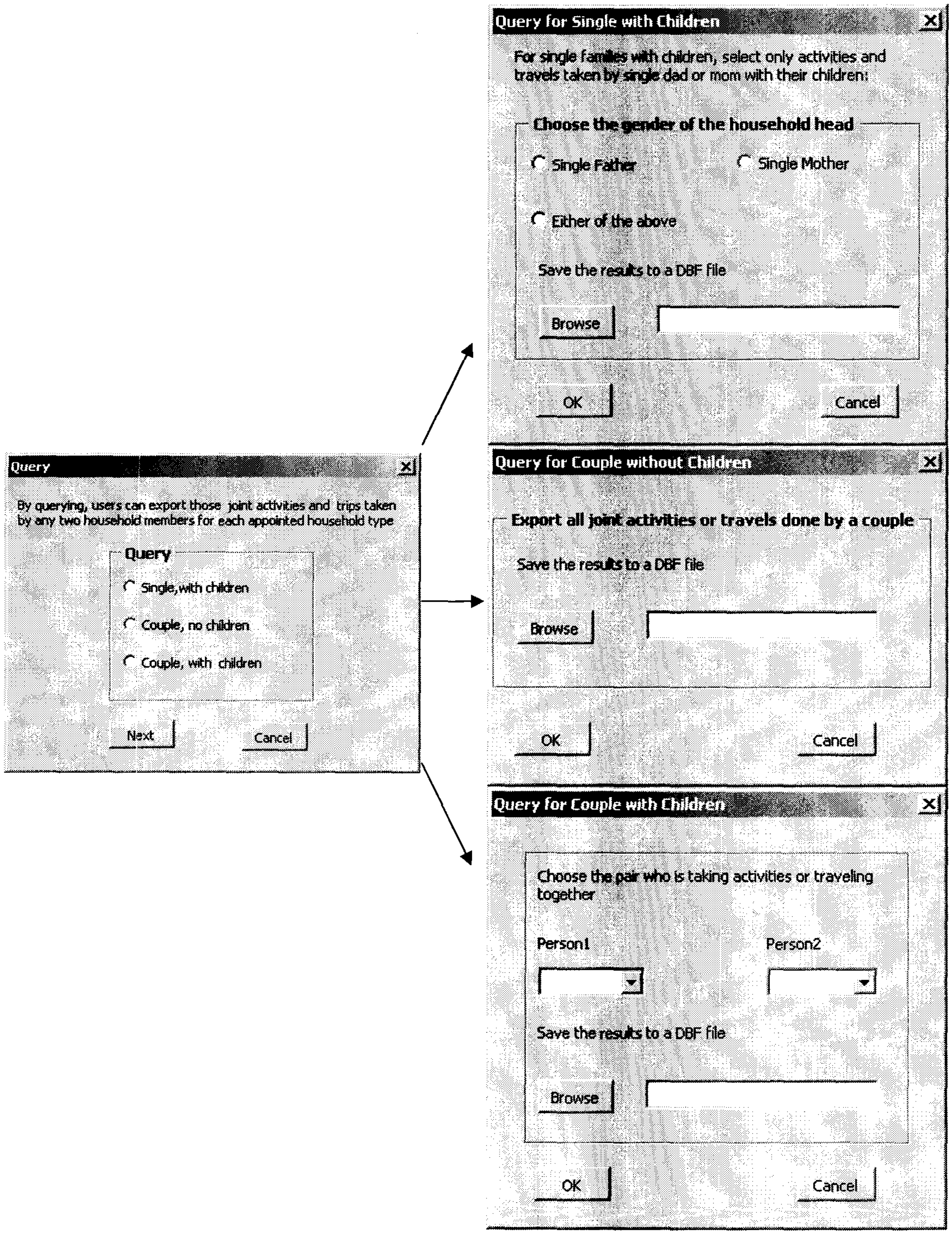


Figure 2.7a-e The interface of the Space-Time Coincidence Analyst tool

Appendix B: Sum of Squares

According to Pas (1987), the total variability is represented by the total sum of squares (TSS), as follows:

$$TSS = \sum_{j} \sum_{i \in M_j} \sum_{k} (t_{ijk} - \bar{t})^2$$

where

TSS is the total sum of squares,

t_{ijk} is the total duration of a given activity type by person i of household j on day k,

$\bar{t}$ is the overall sample average duration of a given activity type per person per day, and

M_j is the set of all persons in household j.

The interpersonal variability and the intrapersonal variability are prescribed by the between-person sum of squares (BPSS) and the within-person sum of squares (WPSS), respectively, defined as follows:

$$BPSS = K \sum_{j} \sum_{i \in M_j} (t_{ijk} - \bar{t})^2$$

and

$$WPSS = \sum_{j} \sum_{i \in M_j} \sum_{k} (t_{ijk} - \bar{t}_{ij})^2$$

where

$BPSS$ is the between-person sum of squares,

$WPSS$ is the within-person sum of squares,

$\bar{t}_{ij}$ is the average duration of a given activity type made per day by person i of household j, and

K is the number of days in the observation period.

Appendix C: Structural Equations Modeling

Following the matrix notation of Lu and Pas (1999), an SEM for observed variables can be defined as:

$$y = By + \Gamma x + \zeta$$

where

B is $p \times p$ matrix of coefficients, representing the direct effects of endogenous variables on other endogenous variables;

Γ is $p \times q$ matrix of coefficients, representing the direct effects of exogenous variables on endogenous variables;

y is a $p \times 1$ vector of endogenous variables;

x is a $q \times 1$ vector of exogenous variables;

ζ is a $p \times 1$ vector of errors in the equations, with the standard assumption that ζ is uncorrelated with x.

In addition to B and Γ, Φ $(q \times q)$ is the covariance matrix of x, and Ψ $(p \times p)$ is the covariance matrix of ζ. As structural equations models are estimated using covariance (structure) analysis, the fundamental idea in estimating the model is that Σ, the population covariance matrix of observed variables x and y, can be expressed by the unknown parameters (B, Γ, Φ, Ψ). Then, these unknown parameters can be estimated through minimizing the discrepancies between the sample (observed) covariance matrix S and the population covariance matrix Σ (Lu and Pas, 1999).