An Activity-Based Travel Needs Model for the Elderly

by

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ABSTRACT

Over the coming decades, a significant increase in the numbers of elderly people requiring travel will occur as the demographic profile of Canadians shifts thereby affecting all aspects of transportation demand. Furthermore, cohort effects are anticipated which may see tomorrow's elderly leading more active lives and travelling to more activities than today's aged. The current lack of a detailed description of elderly travel characteristics and behaviours, particularly one that examines the issue at a level involving activity engagement, was a deficiency addressed by this research. A further product of this study was the development and testing of a simplified activity-based modelling framework. The framework was designed to describe elderly travel characteristics and demand with the added benefit of providing a tool that can evaluate transportation related impacts of proposed policies.

Comparisons of activity participation of the elderly with younger age groups showed that although the daily number of activities remains relatively constant, beginning around age 75 there is a significant decrease in the number to which they travel. There are also significant changes in the types of activities to which the elderly travel compared with the younger age groups. Furthermore, the daily number of trip tours was shown to increase for those 65 to 75 years of age before it steadily declines with advancing age. The average number of activities accessed in each trip tour was found to decrease significantly beginning at about age 65.

Having been traditionally addressed as a relatively homogeneous group by transportation planners, the elderly were shown to possess extremely varied characteristics. Cluster analyses were undertaken to identify subpopulations of the elderly from a sample of 1,150 who responded to an activity-based survey conducted in Portland, Oregon. To identify different lifestyle groups, exploratory analyses were undertaken to delineate clusters based on socio-demographic, travel, and activity engagement variables. The final cluster solution chosen to provide a categorical basis for the modelling framework identified six distinct lifestyle groups based on socio-demographic variables. These clusters were also found to have statistically significant differences in travel behaviour and activity engagement patterns. The clusters identified are characterized as those who remain active in the workforce, the mobility impaired, the elderly who live with their grown offspring, the disabled who drive, and those who either live alone or with a spouse and continue to drive.

The activity-based model was developed using discrete-event, stochastic simulation (or microsimulation) as a platform. Through a sequential process, the model stochastically assigns individuals with a daily

itinerary of activities. Trip tours are estimated based on the type and quantity of activities requiring travel. All model assignments are conditioned on each individual's cluster membership. Although the model is operationalized at a relatively rudimentary level, it provides a base structure that can be enhanced in subsequent versions.

The model framework successfully replicated all facets of the base data set used for its development. Elements of travel behaviour synthesized for individuals being modelling included total daily activities (with and without travel), activities engaged in by class (with and without travel), total daily trip tours, and mode splits. Comparing model outputs with observed base data, both the number of activities requiring travel and the total daily trip tours were overestimated by 3.7 percent for all of the elderly combined. The travel model was also applied to a smaller external data set (data from a different study area not used for model development) for validation. The number of activities requiring travel and the number of trip tours were overestimated by 9.2 and 10.5 percent, respectively. Differences between model outputs and observed values are the combined result of the stochastic nature of the modelling framework, aggregation effects (i.e., assigning individuals to clusters with predefined characteristics), model inaccuracies (e.g., use of regression models to predict the number of trip tours), and an incomplete set of constraining rules which govern daily activity itineraries.

Two test applications of the model explored its ability to evaluate the impacts of a road pricing policy and a mandatory license retesting program on the different segments of the elderly. Results from a stated-adaptation survey for road pricing were used to modify the underlying empirical distributions imbedded in the base model. The model was rerun and the results compared with the original outputs. The analysis allowed the varied impacts of increased travel costs to be compared between the six elderly lifestyle clusters. This first test application illustrated the importance of having a statistically significant sample from a stated-response survey to represent each lifestyle cluster. Future applications should rely on stratified sampling techniques for stated-response surveys.

The second test application examined the potential impacts associated with the implementation of a mandatory relicensing program for those older than 80. Given that the clusters were delineated based on several general socio-demographic variables, the model was not able to isolate fully the activity and travel patterns of this target group based only on age and driver's license variables. The test case reinforced the importance of defining clusters based on the end use of the model. For specific uses of the model, defining clusters on dimensions other than general socio-demographic variables will sometimes be necessary.

The research has provided a more comprehensive understanding of the varied lifestyles, activity patterns, and subsequent travel behaviour and needs of the elderly. Furthermore, it has been shown that a categorical approach using lifestyle groups with unique activity and travel characteristics can be successfully combined within an activity-based framework. Although this approach was applied specifically to the elderly, it can be extended to other heterogeneous groups including the population as a whole. The successful development and validation of a simplified activity-based model have given this field of study a much needed demonstration of an operational activity-based modelling framework. It has been shown that even a simplified framework can synthesize the linkages between activity patterns and corresponding trip-making.

ACKNOWLEDGEMENTS

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CHAPTER 1

INTRODUCTION

Transportation planners are faced with difficult challenges as the North American highway system becomes increasingly more congested. The ability to increase roadway capacity to meet demand is constrained by fiscal and physical limitations. In response, the trend has been to develop and implement travel demand and congestion management schemes through operational policies and technologies.

Traditional transportation analysis models were developed in a context where aggregate forecast volumes were required to plan future capacity requirements on a link by link basis. Today's environment demands a more sophisticated set of models that can reflect individual behavioural response to transportation policy. Legislation such as the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 and the Clean Air Act Amendment (CAAA) of 1990 in the United States has increased the need for more precise and comprehensive travel forecasts to enable state agencies to access "Flexible Funding" options (SG Associates, 1995). Furthermore, planning agencies are striving to integrate high technologies, innovative cost recovery schemes, and safety driven policies into the transportation system. The ability to understand the influence that these policies will have on user behaviour before they are implemented is needed.

This document presents the results of analyses that have developed a better understanding of the travel behaviour characteristics of the elderly. Furthermore, the development of a tool capable of evaluating future travel needs among the elderly is described. Demographic trends show that there will be a proportionately larger increase in the number of elderly over the coming decades as the "baby boomers" reach the age of retirement. More active lifestyles and the desire for continued mobility by future generations of seniors will result in a unique set of requirements for transportation systems. The impact of policies targeted at older travellers to increase mobility or temper driving among those who are physically or cognitively unfit will need to be understood.

The project uses an approach to travel demand analysis termed *activity-based.* Given its behavioural richness and sound theoretical basis, the activity-based approach is currently viewed as the framework with the greatest potential to address complicated relationships between policy implementation and trip-making. The activity-based approach essentially focuses on activity participation as the element of analysis rather than the actual trip (which is viewed as an end-product). Fundamental to the approach is the assembly of daily activity itineraries that respond to external stimuli and constraints thereby changing trip-making behaviour. Depending on the depth and focus of the specific model, the end product can be as simplistic as individual activity itineraries that require travel outside the home to be completed, or as robust as network assigned trips. The study introduces a modelling framework that can either complement or replace traditional modelling processes.

A distinct advantage of the activity-based methodology is that travel is analysed at a very disaggregate level where individual activity participation is used as the foundation to trip-making. The ability to evaluate the impacts of specific policies on travel behaviour is seen as one of the primary attributes of this framework. Operationalization of an activity-based approach and the analysis of elderly travel behaviour are considered key contributions of the study.

To identify the need for the study, the context is set in the remaining sections of this chapter by briefly outlining evolving trends in elderly demographics and travel behaviour. The foundation for the study's approach is established by reviewing travel demand modelling methodologies. The shortcomings in existing approaches are highlighted to formulate the basis for the employment of an activity-based approach. Finally, the dimensions of the problem addressed by the study are defined.

1.1 Elderly Trip-Making

The combined effect of changing demographic and travel behaviour characteristics among the elderly will have a significant influence on the overall makeup of the population of transportation users in coming years. Demographic trends and mobility issues concerning the elderly are outlined in the following sections. Furthermore, public policies that will shape the way the elderly participate in trip-making are identified since the understanding of their impacts was a fundamental impetus behind the development of the model.

1.1.1 Demographic Trends

The provision of safe and affordable transportation for the elderly is becoming an increasingly important and topical issue among transportation planners. The proportion of Canada's total population who are 65 years of age or older was 12 percent (3.2 million) in 1991 and, as shown in Figure 1.1, is projected to nearly double to 22 percent (8.3 million) by the year 2031 (Norland, 1994). This phenomenon is primarily a ripple effect, illustrated in Figure 1.2, which has been generated by the "baby boomers" born in the 1950s and 1960s. Such a drastic increase in the proportion of elderly users of transportation systems is an issue that must be addressed by planners if appropriate services are to be delivered. Furthermore, changing lifestyles (e.g., redistribution to the suburbs, increased incomes, increased proportion and retention of drivers' licenses, etc.) will dictate increased demand for transportation services among the aged. The coexistence of these trends will serve to exacerbate the need for changes to the transportation system to accommodate the elderly.

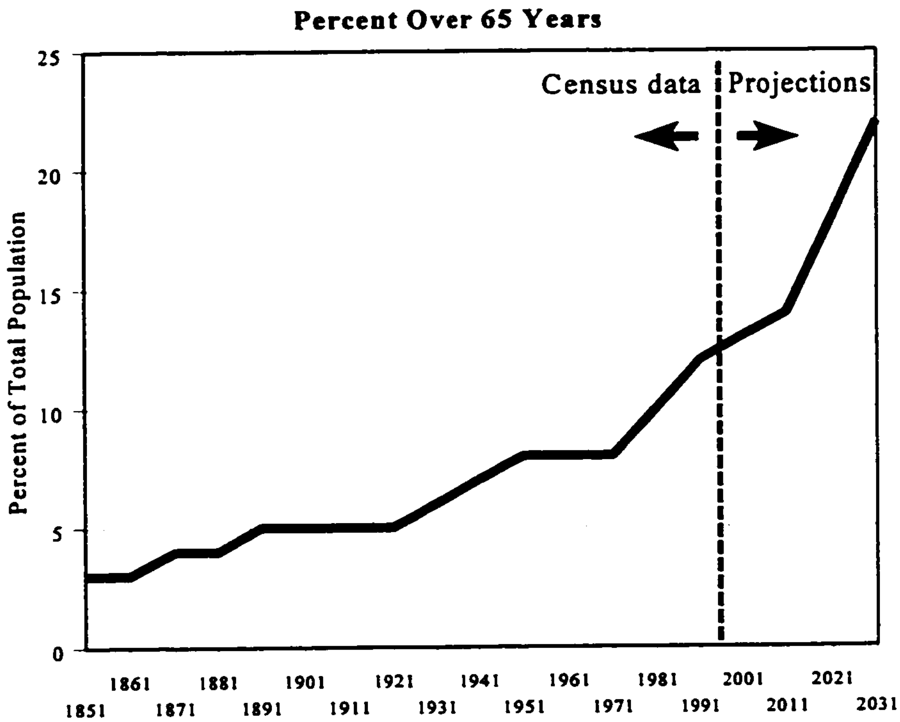

Figure 1.1: The Aged Population of Canada

Source: Statistics Canada -Catalogue No. 96-312E, *Profile of Canada's Seniors*, Ottawa, ON, 1994, p.6.

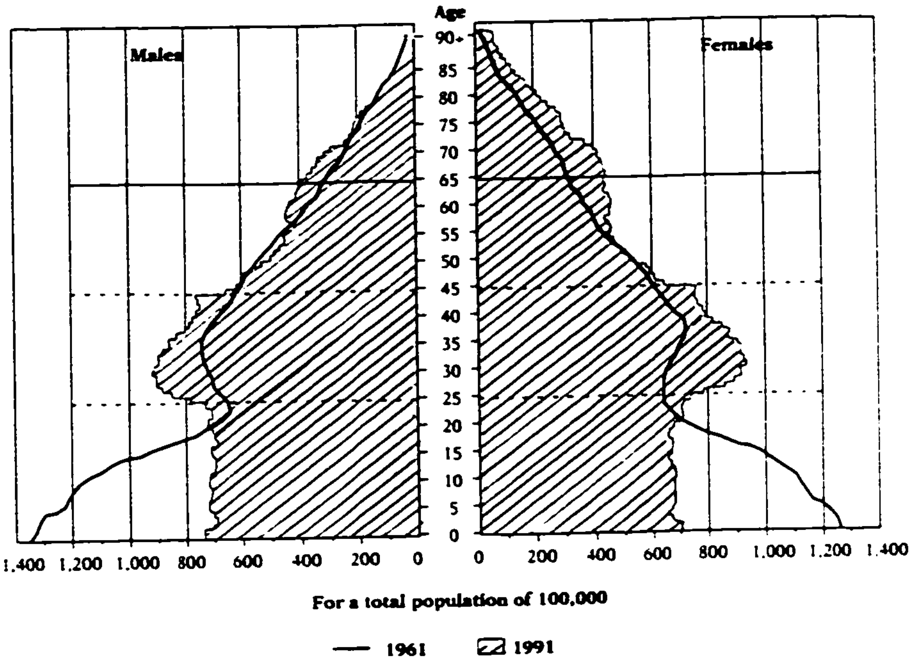

Figure 1.2: Population Distribution by Age and Sex, Canada, 1961 and 1991

Source: Norland, J.A., *Focus on Canada -Profile of Canada's Seniors*, Statistics Canada and Prentice Hall Canada Inc., Scarborough, Ontario, Catalogue No. 96-312E, 1994.

1.1.2 Mobility of the Elderly

The following section highlights the changing rates of trip-making which accompany advancing age. Some underlying influences and associated characteristics of these trends are documented including activity participation, required transportation resources, and accident rates among the elderly.

There is a significant reduction in trip-making which occurs at retirement and beyond. Figure 1.3 illustrates the extent to which trip-making decreases with advancing age. Interestingly, it is shown that the average number of daily trips made by those 75 and older is less than half the rate of those who are of pre-retirement age. Furthermore, the total distance of daily vehicle trips is reduced to only one-third. The mobility patterns of the elderly obviously seem significantly affected by (1) retirement from the work force, and (2) advancing age. A significant portion of the proposed study will explore the interaction of other variables as they relate to this decline in mobility.

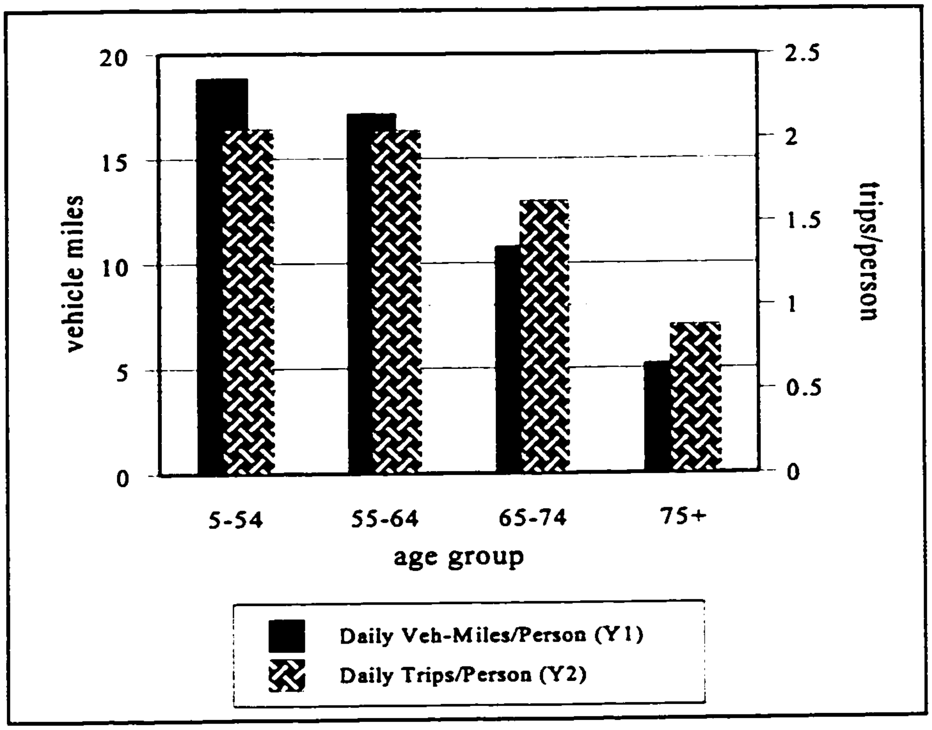

Figure 1.3: Trip Generation Rates

Source: Institute of Transportation Engineers, *Selected Travel Behaviour Characteristics of the Elderly*, Technical Council Committee 6F-50, Washington, D.C., 1994.

Jones *et al* (1983) have shown that not only do the trip rates decrease as age increases, but there is a restructuring of trip purposes as people move through different stages of the lifecycle. Figure 1.4 illustrates the varying trip rates associated with different trip purposes for each of eight lifecycle groups. Group A represents young households without children, B represents the arrival of children, while subsequent groups represent advancing stages including when the children reach school age, when they leave home, until Group H is reached representing both adults at retirement. Mean trip rates for each lifestyle group are represented by the arrowheads in the figure while confidence intervals are depicted by the varying width of the solid lines. Of interest is the large proportion of *other* trips made during the child-rearing years (supposedly linked to serving the activities of the dependents). Little is understood concerning the activities engaged in by the retired which are aggregated and classified simply as *other*.

Although a cross-sectional view of the frequency of elderly trip-making at a particular point in time illustrates an inverse relationship with age, Rosenbloom (1995) found that in the United States there is a longitudinal trend toward increased travel *distance* by older drivers. She noted that "the elderly as

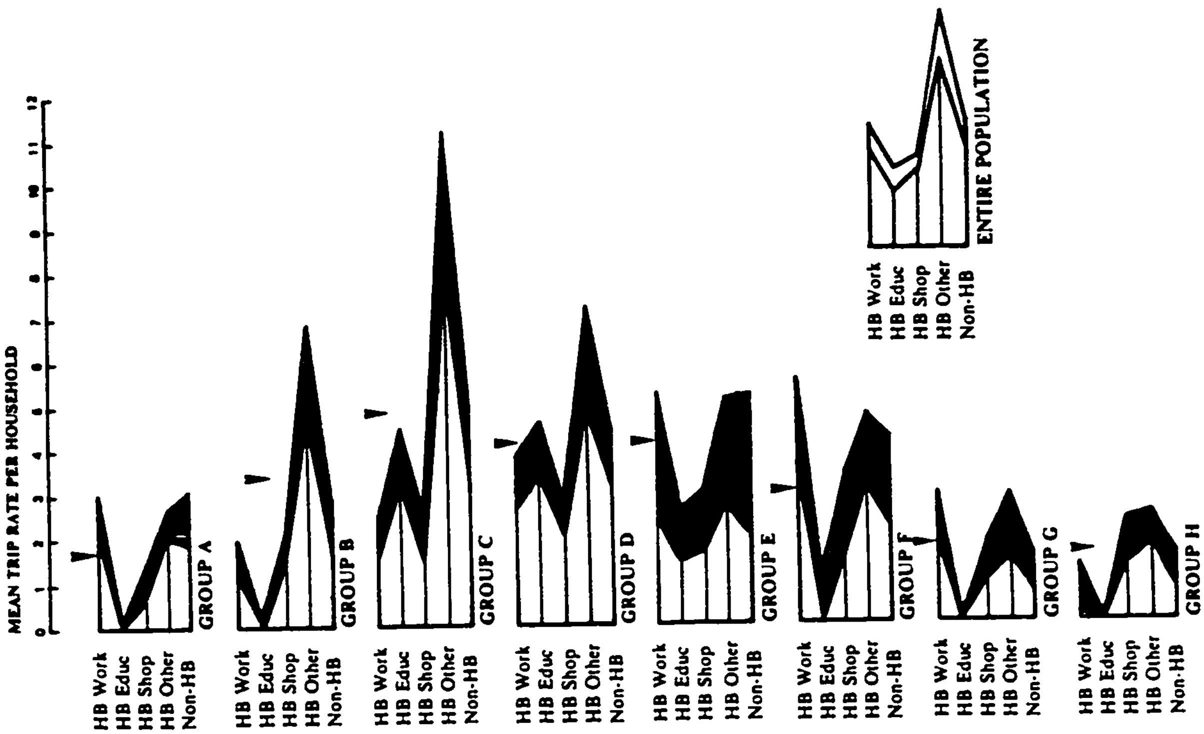

Figure 1.4: Household Trip Rates by Lifecycle Stage

Source: Jones, P.M., M.C. Dix, M.I. Clarke, and I.G. Heggie, *Understanding Travel Behaviour*, Gower, Aldershot, 1983, p.127.

a group drove 20 percent more miles (in 1990) than they had in 1983 while those over 70 drove 40 percent more." Three interesting questions were raised by these findings. First, it is unclear whether increased travel distances depend on choice (i.e., increased participation in discretionary activities) or necessity (e.g., geographic location of mandatory services). A partial explanation is a shift in the residential patterns of the elderly to the suburbs (Transportation Research Board, 1988). This may require longer trips to reach either work or non-work activities that are not in the suburbs. Secondly, it is not known whether changing travel patterns occurring between different sexes, races, and ethnicities will continue. Finally, the extent of travel changes among the aged and whether they will persist beyond the short-term are unclear.

It is anticipated that current and future generations of Canada's seniors will have increased demands for transportation services compared with past generations of the elderly as they choose to participate in more activities outside the home. Studies in the United States show that current generations of the elderly continue to be healthier, more affluent, better educated, more likely to reside in suburban areas or with independent living arrangements, and more dependent on an automobile for transportation than their earlier counterparts (Wachs and Blanchard, 1976). For example, 80 percent of all trips made by those 65 and over are made in automobiles (Transportation Research Board, 1988). These trends, which are expected to continue, will place unique demands on transportation systems as providers strive to meet requirements unique to the elderly.

Household structure is often linked with travel behaviour. Among those more than 55 years of age, the most profound characteristic is the direct relationship between advancing age and the proportion who live alone. Nearly 16 percent of Canadian females between 55-64 years live alone. This proportion rises with age, more than 30 percent for those 65-74, and nearly 50 percent for those 75 years and older (Beaujot *et al*, 1995). Males living alone represent 10, 13, and 20 percent, of the same respective age groups.

It is startling to note that the 1990 General Social Survey conducted by Statistics Canada (Beaujot *et al*, 1995) found that 57 percent of women and more than one-third of the men more than 75 years of age receive informal assistance with transportation needs. Family members and friends are noted as the primary providers of transportation assistance to the aged. It is noted that average vehicle occupancy steadily increases for females in the four age categories presented in Figure 1.3 (from 1.7 occupants to 2.6), while it remains essentially constant for males. The model framework therefore needs to be responsive to the fact that although the primary transportation resource of the elderly is to drive one's own automobile, there is another significant subgroup who also use the automobile *mode*, but do so as passengers.

The distribution of elderly trips by mode shows a heavy reliance on the private vehicle. Nearly 85 percent of trips are made by private vehicle, 9 percent by walking, and only 2.6 percent by either transit or taxi (combined) (Transportation Research Board, 1988). Longitudinal observations over the past 20 years show these distributions to be relatively stable.

Intertwined within evolving elderly demographics are significant cohort effects that will influence travel demand. In 1983, national U.S. statistics showed that among those over 65, about 62 percent had a driver's license (82 percent of males/ 49 percent of females) (Pisarski, 1988). Within only 10 years the proportion was projected to rise to 95 percent (with nearly 80 percent of females being licensed). While such a profound cohort change is significant, successive generations of the elderly are expected to show less dramatic change as the proportions with licenses reach saturation levels.

Older drivers have been shown to experience accident rates as high as those of newly licensed teenagers (Hildebrand and Wilson, 1990). Should this trend continue in concert with an expected increase in the population of elderly and the proportions who retain their driver's license, a significant safety issue may develop (Hildebrand, 1989). Many design standards in use today are based on studies undertaken in the 1940's when only 7 percent of the population was more than 65 years of age. Consequently, factors used in design such as visual acuity, perception/reaction, and walking speeds are biased toward a more youthful population and will be inappropriate in coming years.

1.1.3 Policies Related to Elderly Mobility

There is a need to evaluate proposed policies aimed at addressing unserved or latent travel demand among the elderly, as well as the safety concerns associated with older drivers, so that decision-makers can understand the impacts that might be associated with their implementation. In light of the safety issue posed by older drivers, many jurisdictions are currently reviewing their policies directed at the relicensing regulations for elderly drivers. Many policy measures can be implemented that essentially restrict the freedoms of older drivers shown to be at a higher risk of causing an accident. Conversely, work is being undertaken that addresses the need for increased mobility (through alternatives to driving) and safety among older travellers (Transportation Research Board, 1988). Mobility implications of specific policies either directed toward, or affecting, this age group that will need to be clearly understood include:

(1) Relicensing regulations of elderly drivers (e.g., written, road, and medical tests).

(2) Restrictive driving privileges (e.g., time of day, distance from home, hours of day, road classes, routes).

(3) Enhancement of existing roadway infrastructure to accommodate the elderly (e.g., traffic signs [1], lane markings, etc.).

(4) Development of in-vehicle technologies to aid elderly drivers (e.g., vision enhancement, collision warning, navigation, etc.).

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1 For example, current letter size design standards exceed the visual acuity of about 40% of drivers aged 65-74 (TRB, Special Report #218, 1988, p.4).

(5) Provision/reduction of dedicated public transit/transportation services for the elderly (e.g., *Elderbus*, *dial-a-bus*, subsidized taxi vouchers).
(6) Organized non-work carpools.
(7) Modifications to existing public transit services (e.g., schedules, fares, routes).
(8) Provision of rural public transportation services.
(9) Provision of in-home services (e.g., meals on wheels).
(10) Provision of pedestrian-friendly neighbourhoods. [2]
(11) Regionalisation of social/public services (esp. health care).

In recent years, provincial governments have pursued the regionalisation of public services, such as health care and social services, to reduce costs. The result has been the concentration of centres at fewer locations. Furthermore, many municipal governments have actively pursued amalgamation with adjacent municipalities, again, with the net effect of concentrating public services at fewer locations. The impact of public policies geared toward regionalisation on the travel needs of the elderly must be more clearly understood.

It will also be useful to understand the impact of more general policies on elderly mobility including increased fuel taxes, license and registration fees, reduced subsidies for public transportation, parking fees, tolling, pedestrian friendly neighbourhoods, travel demand policies, Intelligent Transportation Systems (ITS) technologies, mandatory/early retirement, and the advancement of tele-communication applications (e.g., bank/shop from home).

1.2 Travel Demand Modelling

The process of transportation demand modelling has undergone essentially three metamorphoses since the practice initially became widespread in the 1950's. Manheim (1976) recognized the onset of activity-based models at a very early stage and characterised it as "Generation Three". Generation One is the conventional four-stage travel demand models of the 1950's, and Generation Two represents the incorporation of individual choice, or disaggregate models into the four-stage approach.

The first generation of travel demand models was developed primarily in response to a rapidly changing highway transport system during the post-war boom of the late 1940's and 50's. The four stage travel demand models were developed in response to increasing car ownership, suburbanisation of urban

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2 As many as 7-10% of trips are made on foot by the elderly (Rosenbloom, 1990).

centres, and the decentralization of industries. The four discrete steps in the process consist of trip generation, trip distribution, mode split, and traffic assignment. The focus of this methodology permitted the analyst to evaluate peak hour commuter trip-making to establish roadway capacity. The system examined the relationships between travel and exogenous variables describing the characteristics of traffic analysis zones.

Of particular relevance to the proposed study, is that the four-stage approach cannot examine trip-making of specific market segments (e.g., elderly, young drivers, single mothers, unemployed, disabled, etc.) in the context of proposed policy changes. This precludes the ability to evaluate policies either targeted specifically at the elderly (driver relicensing, driving restrictions, public transportation, etc.) or those that will have a direct impact on this group (road pricing, regionalisation of public services, etc.). Since the traditional models are trip-based approaches, the effect of policies on participation in specific activities (which may or may not require transportation resources) cannot be identified. Another key deficiency of aggregate models is their assumption that the exogenous environment is static. Vehicle and car ownership, for example, are often assumed to be constant within traffic analysis zones.

In response to a general dissatisfaction with the capabilities and accuracy of the traditional four-stage travel demand modelling process, planners have sought more reliable tools. Jones *et al* (1990) note that

> "...in some instances the forecasts of trip-based models have proved to be inaccurate, and this seems to be the result of mis-specification: an inappropriate representation of travel behaviour relationships -often through a failure to recognise the existence of linkages among trips, and between trips and activity participation."

The introduction of disaggregate models was the first widespread response to improve modelling techniques. However, this approach has also lead to unsatisfactory results given its inherent limitations to synthesize behavioural relationships, constraints, and the dynamic nature of individual needs, preferences, and desires. A third generation of models, known as the activity-based approach, has evolved which tries to explain trip-making from the perspective that it is a by-product of participation in activities.

Although the activity-based approach to travel demand modelling has been discussed and developed for nearly 20 years, there are many definitions or explanations that attempt to define exactly what activity-based modelling encompasses. Jones *et al* (1990) differentiate the activity-based approach from conventional analyses when they state that

"...the conventional approach to the study of travel behaviour based on single trip (the 'trip-based paradigm') is replaced by a richer, more wholistic, framework in which travel is analysed as daily or multi-day patterns of behaviour, related to and derived from differences in lifestyles and activity participation among the population."

The approach essentially shifts the focus away from the trip as an end-product to concentrate on the underlying generator of trip-making which is activity participation. If, for example, the effect of policy implementation on activity participation can be understood, then a derivative will be a change in travel behaviour. The approach is primarily a search for the causal structure underlying trip-making.

Fundamental to the approach is the consideration of an individual's activity pattern that includes activities, derived trips, scheduling under constraints, and coordination within the household environment (Axhausen, 1990). Furthermore, consideration is given to both in-home and out-of-home activities, and the linkages which exist between them. The substitution of out-of-home activities with in-home activities is expected to play a significant role among the elderly. This is illustrated in Figure 1.4 (as previously presented). There is a fundamental shift from a mathematical/statistical representation of trip-making based on independent variables to the development of a framework that attempts to emulate human decision making and behaviour. A key ingredient of the methodology is the inclusion of disaggregate time-use information (i.e., dissemination of one's daily itinerary of participation in activities into discrete blocks of time).

The activity-based approach was initially postulated as an attempt to overcome the narrow focus of the traditional four-stage technique that emphasizes the commuter peak hour. More emphasis is now being given to demand management and other traffic control measures to accommodate increasing traffic demand. Previous measures that addressed increasing traffic volumes tended to focus on expansion of the infrastructure to provide increased capacity. Through the activity-based approach, the scope of transportation planning is essentially broadened to encompass the relationship between travel and quality of life rather than concentrating specifically on trip-making.

The evolution of Intelligent Transportation Systems (ITS) technologies have fostered a need for planners to understand the impact of proposed measures on travel behaviour, an area beyond the capability of traditional analyses. The use of Travel Demand Management policies and Transportation Control Measures has generated a need to understand the impact of proposed policies before they are implemented. Interest in activity-based methodologies in the United States has increased recently as Metropolitan Planning Organizations (MPO's) position themselves to compete for funding available through the ISTEA and CAAA programs. This has propagated a broad scope to develop activity-based models capable of analysing entire MPO's so that travel demand measures can be evaluated and environmental implications quantified.

Several recent advances as noted by RDC Inc. (1995) have also contributed to the heightened interest in the application of an activity-based approach including:

(1) An accumulation of activity-based research results.

(2) Advances in survey methods (e.g., stated-preference and time-use survey methodologies) and statistical estimation methods.

(3) Advances in computational capabilities and supporting software (database software, GIS, etc.).

Figure 1.5 depicts one interpretation of the activity-based modelling framework. As discussed later in Chapter 2, there are many different interpretations of the approach; however, many of the common components and linkages are shown. Some researchers have proposed an activity approach as a replacement for the trip generation and distribution steps of the four-stage method while others have developed frameworks that replace the traditional approach entirely. Nevertheless, the essence of all activity-based frameworks is that individuals participate in activities that might lead to trip-making satisfied by transport resources. Ettema and Timmermans (1997) note that

> ".... activity-based approaches typically describe which activities people pursue, at what locations, at what times and how these activities are scheduled, given the locations and attributes of destinations, the state of the transportation network, aspects of the institutional context, and their personal and household characteristics."

Many terms introduced in Figure 1.5 need to be defined for clarification. Axhausen (1997) describes an *activity* as

> "...the main business carried out in one spatial setting including any waiting time before the start of the actual activity, while either interacting with the same group of relevant people for that main business or being alone."

Activity engagement is a term that simply refers to the participation of an individual in a specific activity (e.g., shopping, visiting, etc.).

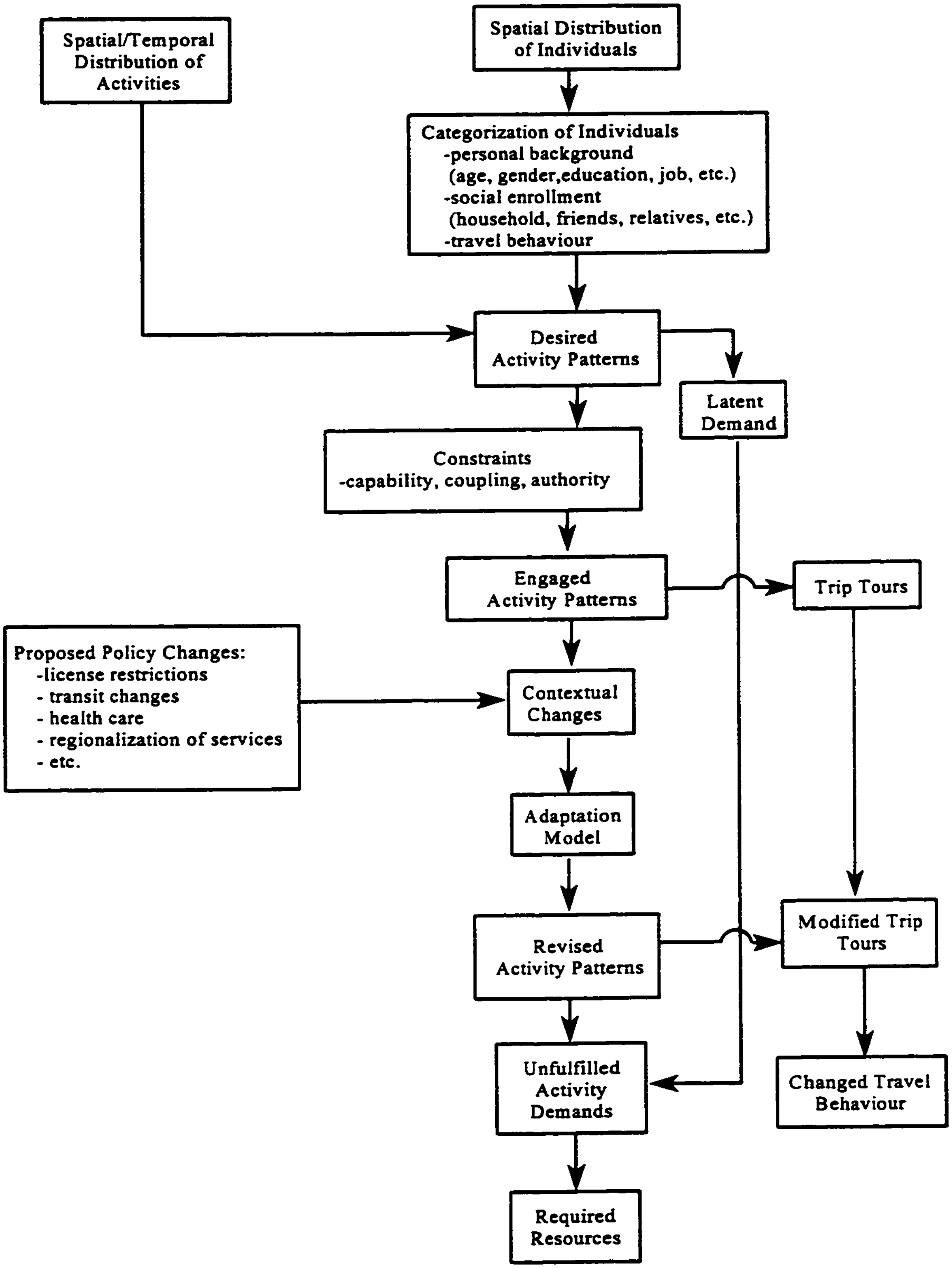

Figure 1.5: Activity-Based Travel Demand Framework

A daily itinerary of individual activities defines the *activity pattern* associated with an individual. For example, typical daily activity patterns have been developed for groups of people with homogeneous socio-demographic characteristics. Activity patterns may be further defined by the ordering and scheduling (place and time) of each element. Note that the activity pattern will include activities that can take place within the home (e.g., eating, personal maintenance, amusement, etc.) and consequently not require travel.

Desired activity patterns represent those activity itineraries which individuals would engage in if no constraints were restricting their participation. *Engaged* activity patterns are those which are actually achieved or realized by an individual once the various layers of constraints are observed. For example, if an individual who is captive to a transit system desires to visit a friend who lives in an area not served by public transportation, the activity cannot be engaged in.

A *trip tour* (sometimes referred to as a chain of activities, or activity chain) defines the collection and sequencing of different activities that require travel, into a linked journey that starts and ends at home. Several trip tours may be made in a given day. A trip tour such as *Home - Shopping - Job - Shopping - Home* implies movement between each activity (e.g., the trip tour would consist of four individual trips: *H S, S J, J S, S H)*. The daily set of trip tours undertaken can be thought of as the *mobility* of the individual.

Figure 1.6 is a representation of different activity patterns for members of a classification of households. The probabilities of engaging in the different categories of activities are depicted by the varying width lines, while an individual activity engagement, and trip tours, are represented by the solid line that traces through a 24-hour period. Alternatively, the lines with the varying widths can be thought of as the changing percentage of people engaging in the various activities listed on the y-axis. Although no scale is given, it can be seen that the proportion of household heads who engage in an *other* activity between the hours of midnight and 8:00 a.m. is high, while there is only a small proportion who work during these hours.

The framework depicted in Figure 1.5 shows how an activity-based approach could be structured to produce a set of daily trip tours for individuals. These trip tours can be developed in response to proposed policy changes and contrasted against base travel behaviour to identify modifications or latent demand. The combination of outputs can be aggregated across individuals to highlight required transportation resources.

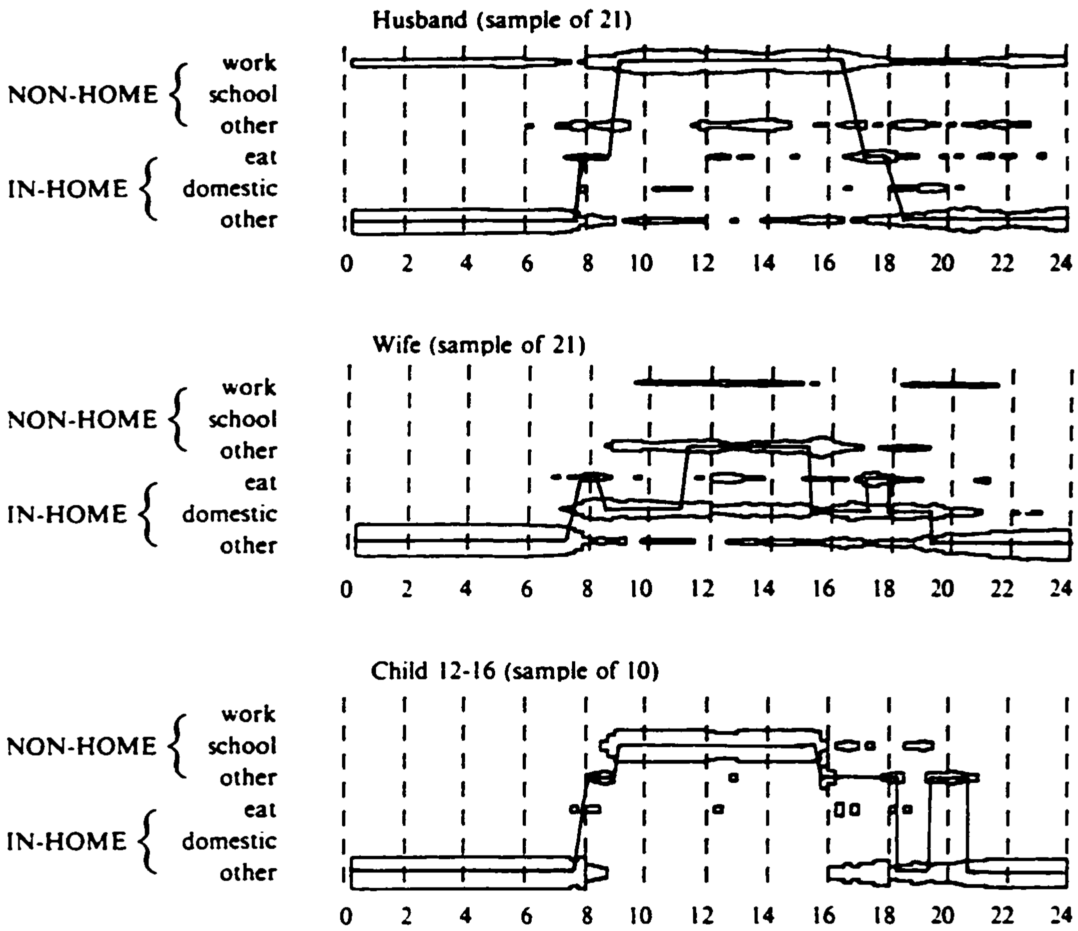

Figure 1.6: Activity Patterns and Trip Tours

Source: Clarke, M.I., M.C. Dix, P.M. Jones, and I.G. Heggie, *Some Recent Developments in Activity-Travel Analysis and Modelling*, in Transportation Research Record 794, Transportation Research Board, Washington, D.C., 1981.

Desired activity patterns are developed for each individual being modelled based on characteristics such as socio-economic variables. Some models will employ "baseline" activity patterns for categories of individuals. The desired activity patterns are then tempered by layers of constraints generally classified as capability (time budget required to eat, sleep, personal care, etc./ distances covered by mode, vehicle availability and transit schedules), coupling (opening hours of service, auto availability, social/household interaction), and authority (restricted access e.g., carpool lane, queuing, etc.). If the model is to be used to quantify policy impacts, there are contextual changes that result from proposed legislation. Several model approaches have been developed which attempt to understand these effects.

The changes in behaviour manifest as revised activity patterns (either changed order, inclusion/substitution, or access) which are then reassembled into modified trip tours potentially placing different demands on transportation resources.

1.3 Problem Definition

Previous sections of this thesis have identified a number of issues that in combination generate a need to be able to analyse travel demand of the elderly. In summary, these issues include:

(1) Rapidly growing number of elderly users of transportation systems.
(2) Changing socio-demographic characteristics of the elderly.
(3) Increased demand for mobility by seniors to engage in activities outside the home.
(4) Growing awareness of the safety implications associated with elderly drivers.
(5) Rising proportion of elderly who will maintain their driver's license.
(6) Current fiscal pressure to reduce subsidies to public transportation systems/services.
(7) Regionalisation of public service centres that are particularly sensitive to the needs of the elderly.

There are currently no comprehensive travel models that have been developed specifically for the elderly. The little research that has been conducted has concentrated on travel demand for rural public transportation services for the disabled and elderly (see section 2.3). There has also been only limited research that has examined general travel patterns of the elderly and little is understood concerning the underlying needs and desires for travel.

1.4 Research Goals and Scope

The issues identified in the previous sections have lead to the formulation of the primary goals of this research:

(1) To develop a better understanding of the current travel behaviour and transportation needs of the elderly.

(2) To develop a simplified activity-based modelling framework for the elderly. The model will be capable of describing elderly travel characteristics and demand with the added dimension of providing a tool to evaluate the transportation related impacts of proposed policies.

(3) To develop and test the primary modules of the proposed activity-based model for the elderly.

The current lack of a detailed description of elderly travel characteristics and behaviours, particularly one that examines the issue at a level involving activity-engagement, will be addressed by the initial goal. Given evolving demographic trends, a better understanding is clearly needed.

As noted, a fundamental goal of the study is to develop a simplified operational activity-based trip-generation model. Jones *et al* (1990) highlight the need to demonstrate the activity-based approach when they say that:

> "Two important challenges face activity analysis at the end of the eighties. The first covers theoretical and methodological issues: to clarify concepts, refine methods and simplify the approaches so far developed to make them more accessible to other analysts. The second is to demonstrate the practical usefulness of these approaches, with particular emphasis on the improved ability to understand and predict travel behaviour in a manner which enhances transportation service decision-making."

Although this statement was made in 1988, it is still applicable today.

Ettema and Timmermans (1997) seem to support the development of smaller, more focussed models when they question the legitimacy of designing large-scale, complex, models by asking whether they

> " ....can be justified because they may provide the required integration, improved prediction, more flexibility and the new kind of information required to assess new transportation policies or that a strategy of building small scale, dedicated models which are deployed with particular policies in mind would be more productive."

Similar sentiments were made at a recent conference where the need to demonstrate real world applications of activity-based models was expressed (Federal Highway Administration, 1997). A model capable of revealing the transportation related impacts of proposed policies could be used to test the effect of different mitigation scenarios on older travellers to ensure a reasonable level of mobility. The proposed model structure can evaluate these types of instruments.

A laudable goal would be to develop a model that would encompass all age groups of the general population rather than just the elderly. In fact, most current developmental efforts of an activity-based approach focus on the weekday commuter to evaluate congestion management techniques. However, it was necessary to limit the scope of this project to make it feasible, otherwise, the data collection and model development effort would have become too onerous. The intent is to demonstrate the capabilities of such an approach and to implement a framework that can be expanded to include all age groups. Using a heterogenous population subgroup ensures that techniques necessary to handle a wider range of the general population are embedded in the framework.

The model is founded on activity-based diary information extracted from a sample of the elderly. For the purposes of this study, the elderly will include all of those aged 65 years and over. This threshold is chosen to coincide with the profound lifestyle changes which accompany retirement.

The data set developed by the 1994/95 Portland, Oregon, Household Activity and Stated Preference Survey was used by this study (Cambridge Systematics, 1996). The data set includes detailed information regarding activity participation of 10,048 individuals. Among the respondents, there are 1,150 who are 65 years of age and over. Since each respondent described activity participation for a two-day period, there are 2,300 person-days of information for elderly travellers.

The transformation of activities into trips or trip tours is a very complicated goal. At issue are factors such as order and scheduling of activities, grouping of activities into trip tours, route selection, mode choice, intra-household requirements, etc. Restricting these decisions are coupling, capability, or authority constraints, as previously described (Bowman and Ben-Akiva, 1997). Furthermore, network specific factors such as congestion and travel times will also influence the assembly of activities into trip tours. It was not the intent of this research to explore the complicated decision-making process underlying the assembly of activities into trip tours. Given that the fundamental intent of the model was to develop a tool to explore the travel behaviour and needs of the elderly, it was sufficient as a first step to formulate the gross effects of policy reaction mainly in terms of participation in activities. The aggregation of individual activities into tours is dealt with in a simplified manner for the purposes of this study. The rationale for this restriction is discussed in ensuing sections.

Other issues that were beyond the scope of the project include the issue of geographic transferability of the model (to different sized urban centres or rural areas) and its extension to the overall population, rather than just the elderly.

1.5 Thesis Organization

This thesis is organized into eight chapters. Chapter 2 develops the theoretical foundation of the research by reviewing the current state of traditional and activity-based travel demand modelling. The existing understanding of elderly travel behaviour is reviewed to identify deficient areas. Techniques in microsimulation and categorical stratification are reviewed to provide background to the analytical techniques that were used.

Chapter 3 frames the approach and methodology employed in the development of the four modules of the activity-based model. Issues associated with model validation and test runs are also discussed. Chapter 4 develops a cross-sectional comparison of activity engagement and resulting travel behaviour of the elderly with younger age groups. The analysis uses data captured in a recent activity-based survey. The results provide a better understanding of the travel needs of the elderly and establish a benchmark against which the patterns of homogeneous subgroups can be compared.

Chapter 5 presents the results of cluster analyses that delineated lifestyle groups among the elderly. The clusters were defined on the basis of socio-demographic, activity engagement, and travel behaviour characteristics.

The development of an activity-based microsimulation model is described in Chapter 6. Inclusion of lifestyle groups, module development and the results of test runs made for validation are presented. Chapter 7 uses a data set of stated-adaptation responses to road pricing scenarios as a test application of the model. A further test application examines the implications associated with a mandatory retesting program for the elderly renewing their driver's license. Finally, study conclusions and recommendations are listed in Chapter 8.

CHAPTER 2

LITERATURE REVIEW

The literature review undertaken in support of this study is presented in five main sections, namely: traditional travel demand models, activity-based models, elderly travel demand, discrete-event microsimulation, and categorical stratification. A brief review and critique of traditional travel demand models are presented to highlight their inability to deal with the problem at hand. Past and current development of activity-based models are critiqued in the context of their abilities to deal with a specific user group such as the elderly. What little research that has been done regarding the travel needs of the elderly is summarized to emphasize the need for more work in this area. The use of microsimulation as a platform for an activity-based framework is discussed as an extension to the discussion of developed models. Finally, techniques that exist to stratify transportation users into homogeneous groups are presented since it is proposed to incorporate categorical analyses into the activity approach.

2.1 Traditional Transportation Demand Models

An extensive body of literature exists that describes the different modelling approaches used to describe travel demand. It is not the intent of the proposed research project to undertake an exhaustive critique of travel demand modelling techniques but it is vital to understand which approaches have been developed and to identify their respective advantages and shortcomings.

Nearly all travel demand models or approaches are based on the four-step procedure (trip generation, trip distribution, mode choice, and trip assignment) developed in the 1950's and 1960's. The trip generation models developed for the early travel demand techniques relied almost exclusively on regression models or category analyses. Relationships were drawn between trip-making and zonal characteristics such as population, income, car ownership, household size and structure, and commercial activity. Models typically used data that was available on a zonal aggregate basis through the census.

Trip distribution models were developed to synthesize the travel matrix of origins and destinations that trip-making produces. The most common approach utilized was the gravity model which relates the trip-making between two specific zones in proportion to their trip generation and the spatial separation of the zones.

Early mode choice models were able to estimate modal splits in a single stage using models based on socio-demographic and mode service variables. Perhaps the most common approach has been to use binary choice stochastic modal split models such as those used in discriminant, probit, and logit analyses. Use of disaggregate choice models requires that results be aggregated to the zonal level for use in the four-stage process.

The final stage, trip assignment, simulates the way travellers route themselves on the transportation network when travelling between origins and destinations. Hutchinson (1974) noted that a number of techniques have been developed but that all "techniques contain the following three components: a driver route-selection criterion, a tree building technique that selects a vehicle route through a network of streets, and a method of allocating vehicle trip interchanges between these routes."

While the four-step approach was sufficient at a time when capacity analysis of an expanding infrastructure base was the focus, it has come under increasing criticism given its inability to deal with current planning issues such as Travel Demand Management (TDM) and Transportation Control Measures (TCM). Although the impacts of most TDM and TCM policies on the elderly are not a primary concern, it is the inability to deal with a proposed policy that is relevant.

The four-step approach is not without its advantages. It makes use of standard survey methods, existing census data, and has become relatively standardized through the development of a PC-based planning package called Urban Transportation Planning System (UTPS). In fact, the penetration of this standardized approach will be a significant obstacle to the introduction of the next generation of methodologies.

While no single framework can accommodate all study objectives, the most fundamental drawbacks of the four-step approach include (RDC Inc., 1995):

(1) Internal inconsistencies.
(2) Data inefficiency.

(3) Lack of behavioural foundation.
(4) Inability to evaluate policy.

Although it may be possible to address specific deficiencies within sub-models of the four-step approach by introducing new elements, the basic framework of this approach, and its reliance on the *trip* as the fundamental element of analysis, impedes its ability to overcome fundamental shortcomings.

Given the level of zonal aggregation often used in the four-step approach, a number of methodological inconsistencies have been identified. Zonal trip productions usually do not match trip attractions and must be adjusted. Intra-zonal trip-making is often not well understood. Estimated travel times used for trip distribution and mode choice are not necessarily consistent with those associated with trip assignment (although feedback loops can partially address this issue). By treating each individual trip as a separate entity, inconsistencies arise when mode choice is developed for trip chains with several stops (e.g., home to work by car, work to shopping by bus, shopping to home by train). Modal continuity is ignored and the behavioural characteristic of choosing a mode while considering the chain as a whole is ignored. This ultimately leads to an overestimation of mode changes.

Aggregation of data into zonal averages makes inefficient use of available data. With the development of increased computational abilities, disaggregate mode choice models have at least partially addressed this issue. However, as Khan (1985) notes, despite it being a more desirable approach, the disaggregate models developed to date have several drawbacks including: over use of proxy variables (eg., income as a measure of affluence); insufficient attention given to context of behaviour; lack of emphasis on interdependence of constraints and preferences; inadequate treatment of non-economic factors; exclusion of system reliability, comfort, convenience, and other characteristics; and, neglect of dynamic nature of individual needs, preferences, and resources.

Lack of behavioural realism is a key issue that is seen to limit traditional travel models from being able to properly deal with *cause and effect* analyses. Often, implicit assumptions are made which lack any behavioural foundation. For example, many trip generation models use the number of household members as an independent variable but neglect the behavioural fact that employment status affects trip-making. Many sub-models of the four-step process have, in fact, been *descriptive* which as Rice *et al* (1981) describe as those "which only seek to describe an existing situation and are totally devoid of any causal relationships. They are often stratified by trip characteristics (purpose, length, time of day) and/or traveller characteristics (market segments as defined by income, sex, age, etc.)."

The lack of inter-connectivity between the sub-models of the four-step process creates an impediment to its use for policy analysis. For example, trip generation is typically insensitive to congestion levels (when applying the four-step approach) so policies geared to congestion management would not affect levels of trip-making.

An absence of time dimension in the four-step process implies that departure time is not a choice among trip-makers. While this may be appropriate for evaluating infrastructure capacity, it is restrictive in the context of the elderly who often travel during off-peak periods given a more flexible lifestyle.

In summary, the following limitations of the traditional four-step approach are cited as impediments to its use for policy evaluation (RDC Inc., 1995):

(1) Trip-based, sequential structure.
(2) Lack of the time-of-day dimension.
(3) Limited sets of explanatory variables.
(4) Limited behavioural responses.
(5) Consequently unresponsive to most TDM measures.
(6) Trip generation unresponsive to congestion pricing.
(7) Consequently the trip distribution phase is not fully responsive to system change.
(8) Inability to address vehicle fleet mix evolution.
(9) Totally exogenous land-use, economic and socio-demographic input.

In the context of this study it was therefore necessary to employ an alternative modelling framework for the analysis of elderly travel behaviour if the effects of relevant policies are to be understood ahead of their implementation.

2.2 Activity-Based Models

A review of the development, advantages, and disadvantages of the activity-based modelling approach is presented followed by a critique of existing models/frameworks.

2.2.1 General

Much of the previous research concerning activity-based modelling has concentrated on the development of a framework for its operationalization. Although it is considered a more wholistic and theoretically robust approach, relatively little work has been undertaken to advance its use in practice due, in part, to the complexities inherent in the methodology. The advancement of the activity-based approach has been, until recently, an academic pursuit.

Although research efforts have varied considerably in terms of style and content, key features of the activity-based approach are outlined by Jones *et al* (1990) which include:

(1) Explicit treatment of travel as a derived demand (while recognizing that, on occasions, travel may be a primary activity in its own right).
(2) Focus on sequences or patterns of behaviour rather than an analysis of discrete trips.
(3) Emphasis on decision-making in a household context, taking explicit account of linkages and interactions among household members.
(4) Emphasis on the detailed timing as well as the duration of activity and travel, rather than using the simple categorization of 'peak' and 'off peak' events.
(5) Explicit consideration of spatial, temporal and interpersonal constraints on travel and location choices.
(6) Recognition of the interdependencies among events that occur at different times, involve different people, and occur in different places.
(7) Use of household and person classification schemes (e.g., stage in family life cycle), based on differences in activity needs, commitments and constraints.

In addition to the key elements of the activity-based approach noted above, generic advantages are highlighted as follows:

(1) Recognition of the complexity of travel/activity behaviour rather than merely trying to mathematically replicate travel patterns through statistical associations.
(2) An ability to reflect policy implications in forecasts including various constraints.
(3) Activity-based models can be developed to incorporate supply characteristics.
(4) An ability to deal with a heterogeneous society.
(5) Treatment of linkage between activities and hence trip tours, rather than dealing with trip segments (i.e., travel to a single destination) individually.
(6) Flexibility (i.e., can analyse various policy implications with results from specific stated-preference surveys).
(7) Inclusion of induced demand.
(8) Temporal coverage (i.e., not limited to cross-sectional or peak hour analyses).

A key advantage that is directly related to this proposed research, noted by Kostyniuk (1988), is that the activity-based approach has "a great potential in helping to sort out travel behaviour of the anticipated large cohort of elderly Americans." She goes on to say that "activity analysis could be a good starting point for sorting out the effects of age, aging, and previous automobile use on the travel behaviour of this important group." The implication is that some relatively complex interrelationship will be at work as the profile of the elderly changes in response to demographic trends and past life experiences. For example, tomorrow's elderly will have lived lives where automobile usage was essential to pursue many daily activities. Their travel habits and expectations may be much more demanding and complex than the current generation of the elderly.

An important aspect that should temper the proposed research is that the activity-based approach's

> "greatest present and potential impact and role is in understanding the diversity of travel and activity patterns, detecting subpopulations with quantitatively different transport needs, and identifying situations where the significance of some of these diverse and nonstandard patterns limits the applicability or requires the revision of or updating of travel demand forecasting models" (Mamassani, 1988).

Kostyniuk (1988) echos the idea by noting that the activity-based approach is "an approach or a philosophy for exploring travel behaviour rather than a methodology ready for 'turnkey' estimation of travel demand." Although a turnkey approach is needed to put newer, more appropriate, methodologies into practice, the initial step must be a fuller understanding of travel behaviour. To date, there have been no studies that have applied an activity-based technique to a user specific group in order to gain a better understanding of their travel behaviour and responsiveness to policy implementation.

Some of the more significant disadvantages facing the implementation of the activity-based technique include:

(1) Simplification required to reduce the number of combinations for the production of an activity schedule (e.g., number of activities, sequencing, grouping into trips, etc.).
(2) Difficulty in analysing activity engagement given the microscopic complexities of human decision-making and behaviour.
(3) Increased demand for data -conventional trip diaries are insufficient.
(4) Absence of successful demonstration of the technique in practice.
(5) Lack of a common methodological framework for its implementation.
(6) Difficulties in validation of the approach (most uses propose to evaluate the impacts of proposed policies that will be unknown until actual implementation).

(7) Ability to interface with existing methodologies is unknown.

(8) Transferability is unknown.

(9) Inertia and training required to displace current practices.

Throughout the past 20 years many activity-based planning models have been proposed, some developed, but few actually brought to a functional state. Much of the work to date has been conceptual in nature as planners struggle to develop an appropriate framework. Many of the frameworks that have been conceptualized can be broadly categorized as either *time-geographic, activity-choice*, or *dynamic* (Axhausen, 1990). Time-geographic frameworks of human activity and travel behaviour strive to detail the path an individual takes through a day in both space and time. A series of constraints (capability, coupling, and authority -as noted in Section 2.1) restrict temporal and spatial characteristics of the trip-making. Figure 2.1 depicts the path a traveller makes through the course of a day. The x-y plane of the figure shows the path of a person as they travel from home, to the work place, to the bank, back to work, to the post office, and finally back to home. The duration of the activities and trip time are represented in the z-axis of the figure. The time-geographic taxonomy of models fit the top-half of the generic framework presented in Figure 1.5 quite well. The blocks of Spatial/Temporal Distribution of Activities, Spatial Distribution of Individuals, Desired Activity Patterns, Constraints, and Trip Tours are all incorporated. Time-geographic models do not, however, typically deal with forecasting issues or the inclusion of policy effects.

Activity-choice models employ utility maximization techniques to optimize the benefits derived from an activity-pattern synthesized for an individual. All activities performed yield a certain amount of satisfaction referred to in micro-economic theories as utility. The utility depends on the activity's characteristics, type, duration, location, and frequency. Travel to reach the activity can be considered a negative yield, or disutility. The approach has individuals maximize the utility of their total activity pattern under time and money constraints. Activity-choice models are closely related to the Demand Activity Patterns, and Adaptation Model blocks of the framework identified in Figure 1.5.

Finally, dynamic frameworks for activity-based approaches attempt to organize an activity pattern through the course of a day or over longer periods. Some dynamic frameworks concentrate on the pre-travel stage of activity engagement while others attempt to conceptualize the planning and thought process behind the scheduling of activities chosen to satisfy their needs and desires. The travel stage of the model, allows for modifications to the activity pattern given unexpected outcomes such as road incidences (accidents, congestion, etc.) or demands from others. These models would operationalize the Desired Activity Patterns and Trip Tours blocks of the framework depicted in Figure 1.5.

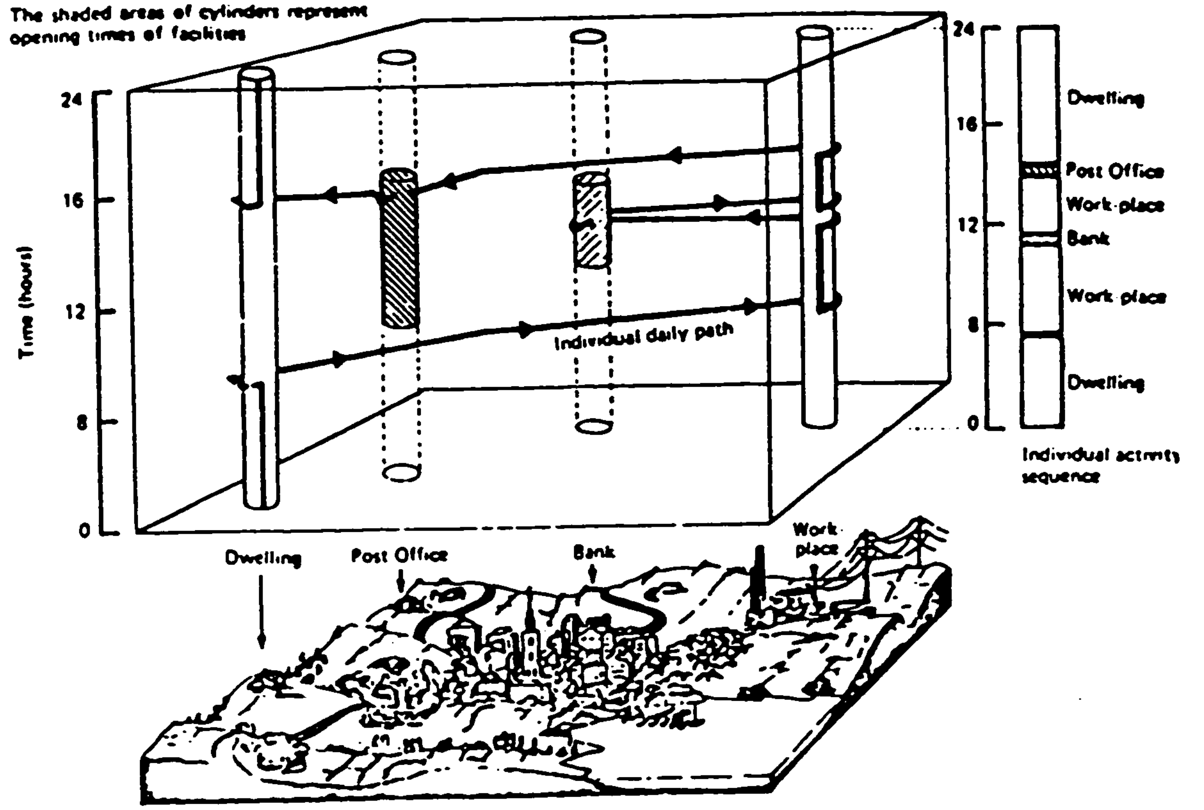

Figure 2.1: Time-Geographic Framework

Source: Axhausen, Kay W., *An Introduction to the 'Activity Approach' -Lecture Notes*, Oxford University, Transport Studies Unit, March, 1990, p.16.

Other dynamic frameworks have a much broader temporal scope as they follow individuals through a whole life-cycle rather than a single day. Activity participation is varied in response to changes in household structure and individual needs/desires as circumstances change through a life-cycle (education, job, marriage, children, unemployment, retirement, etc.).

Activity-based models can also be categorized as either *synthetic* or *switching* models. A synthetic model constructs activity itineraries by assembling individual activities. Conversely, a switching model starts with a predefined schedule and modifies it in response to proposed policy initiatives. Switching models are probably best suited to those with strongly habitual travel patterns (e.g., weekday commuter).

Finally, a coarse taxonomy of activity-based frameworks divides those approaches that use an *econometric* approach to develop activity patterns from simulation or heuristic rule-based methodologies. Econometric techniques tend to employ utility maximization or structural equations models to assemble activity itineraries. Simulation techniques normally rely on stochastic methods (e.g., Monte Carlo) or *common sense* logic rules which govern assignment and scheduling of activity itineraries to individuals.

2.2.2 Review of Existing Activity-Based Models

A few of the landmark models that have gone beyond conceptualization and have actually been developed are described to provide background to the proposed research.

The Transport Studies Unit at Oxford University developed the Household Activity Travel Simulator (HATS) in the late 1970's (Jones *et al.* 1983). HATS can be thought of as essentially a home interview instrument or survey tool that is used to solicit stated responses or adaptations. It relies on gaming simulation techniques to predict how households will adapt to proposed changes in the transport environment. A map of the study area is mounted on a display board and blank daily timetables are presented to the respondents. The locations and times of the individual's daily activities are recorded, then the respondent can rearrange activities on the displays in response to proposed policies. HATS has been used in numerous studies around the world to test the effects of specific policies on travel behaviour. The technique originally used a wooden display board and markers but has since been adapted for use with portable computers (Jones *et al.* 1989).

Models designed explicitly to generate activity patterns or itineraries have provided a step toward the full implementation of an activity-based approach. The STARCHILD model, developed in the mid 1980's, utilizes five separate modules including (Recker *et al.* 1986):

(1) An activity chain is generated for each household member using Monte-Carlo simulation. Constraints for timing, location, and household interactions are incorporated.

(2) A scheduling algorithm is used to establish all feasible patterns of the initial activity itinerary.

(3) Mathematical recognition techniques reduce the feasible patterns to a set of relevant and distinguishable patterns.

(4) Multi-dimensional programming techniques exclude inferior activity patterns based on user specified criteria.

(5) Utility function selects the best activity pattern based on travel time elements, time spent at home, and risk measures for the ability to participate in unplanned activities or for the possibility of being unable to participate in important activities.

Although it is currently the only known operational activity pattern model, it has many limitations including that it does not provide for interaction within a household (a particularly crucial element among the elderly), it relies on a heuristic solution process, and does not allow for complex mode choices. Furthermore, complexity of the system is prohibitive for many applications. This model addresses the Desired Activity Patterns, Constraints, and Engaged Activity Patterns modules of the framework outlined in Figure 1.5.

A similar activity scheduling model known as CARLA was developed by Clarke, in the early 1980's, at Oxford University (Axhausen, 1990). A flow diagram of CARLA is depicted in Figure 2.2. Unlike STARCHILD, CARLA does not concern itself with the prediction of individual activities within an activity pattern, rather it aims to predict the rescheduling of a known activity program in response to changes in service or policy based on a set of heuristic rules and objective functions. It could therefore be thought of as the Adaptation Model component of the framework previously described in Figure 1.5. The heuristic rules include logical (e.g., cannot be in two places simultaneously), time-space (travel times, locations, business hours), and interpersonal and personal rules. The model has been found to be very sensitive to both the length of time blocks, into which the activities are divided, and to the number of constraints (Axhausen, 1990). Although it has potential for use as a tool to evaluate proposed policies, it has not been fully operationalized. CARLA utilizes prototypical activity patterns for individual households that are categorized according to one of eight specific life-cycle groups (one of which is those who are retired) (Clarke *et al*, 1981).

Sparman's ORIENT model (1980) uses Monte-Carlo simulation techniques to assign stochastically individual characteristics (including home location and membership to a homogeneous group) and an activity pattern (defined a priori) (Axhausen, 1990). Specific destinations and modes are then chosen based on inherent constraints so that the activity itinerary can be achieved. Probability distributions are based on either empirical results or more conventional econometric decision models. This approach lacks behavioural realism, dynamic capabilities, and the ability to incorporate policy impacts. The model addresses the Categorization of Individuals, Engaged Activity Patterns, and Trip Tours modules of the overall framework presented in Figure 1.5.

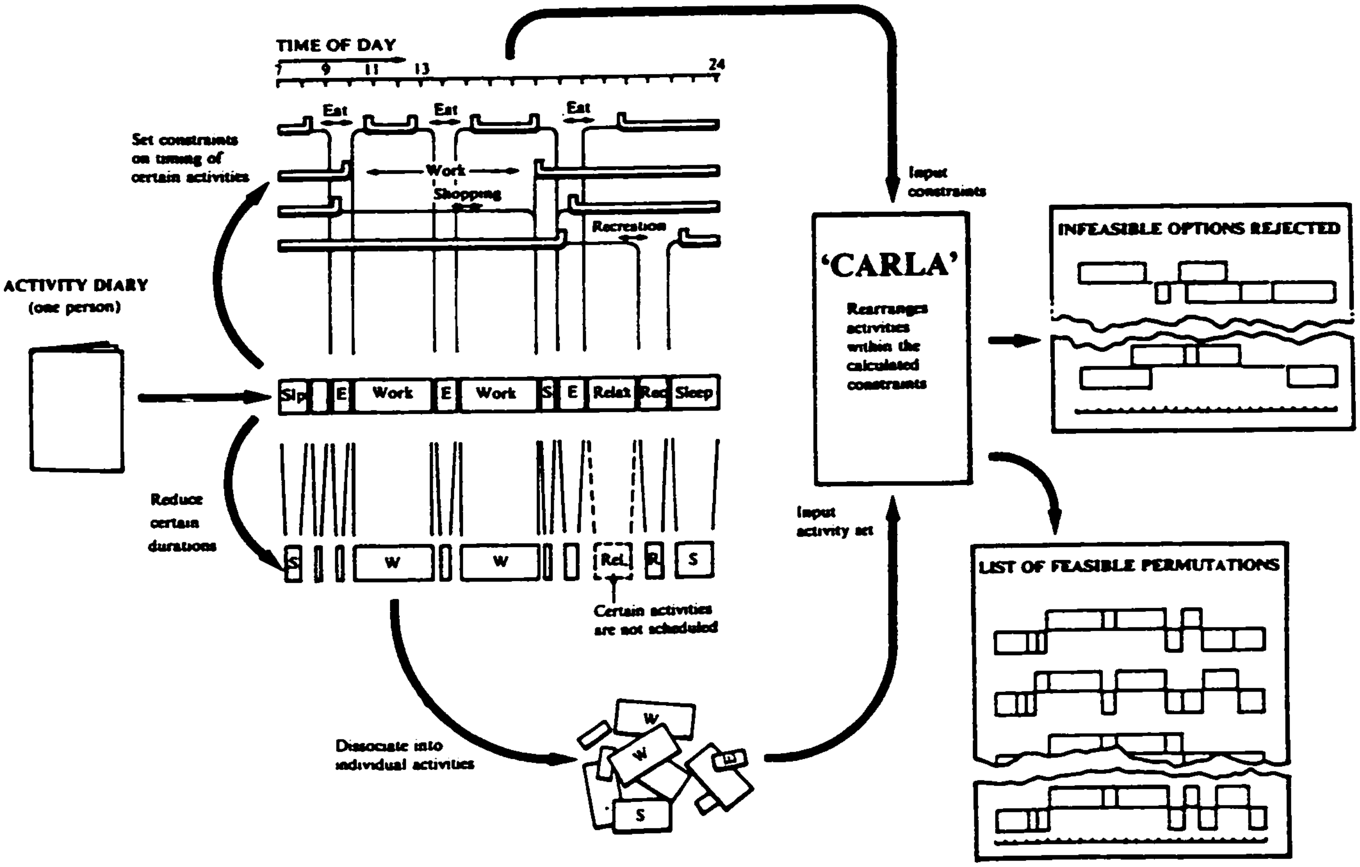

Figure 2.2: Schematic Representation of CARLA

Source: Jones, P.M., M.C. Dix, M.I. Clarke, *Understanding Travel Behaviour*, Transport Studies Unit, Oxford University, Gower Publishing Company Limited, Aldershot, England, 1983, p.202.

The VISEM model has extended a similar approach into practice (Fellendorf *et al*, 1997). The VISEM system essentially replaces the first three steps of the traditional four-stage approach. The main modules include generators of activity patterns, trip chains (tours), and mode choice. The primary units of the model are homogeneous groups of individuals (seven were identified, primarily dependent on employment status and vehicle availability) rather than discrete trip-makers. Individuals are aggregated into groups primarily to ease the computational burden and to facilitate the calibration. Traffic analysis zones are delineated and the above modules applied to each. Empirical probability distributions are used with Monte-Carlo simulation techniques for the first two modules, while mode choice is estimated using nested logit models. While the approach provides a quick response technique, the high level of aggregation restricts its usefulness to examine the needs of specific user groups.

A Simulation Model of Activity Scheduling Heuristics (SMASH) is currently under development in The Netherlands (Ettema *et al,* 1996). SMASH is a model that deals with the formulation and scheduling of the activity pattern prior to the individual actually undertaking the trip tour. The model incorporates aspects of discrete choice modelling (specifically utility maximization) with computational process models (rule based -e.g., *if-then* rules). SMASH does not attempt to describe the details of the trip tours derived from the activity patterns (such as STARCHILD); rather it only tries to replicate the decision-making process that takes place ahead of trip-making.

The actual execution of the trip tour may in fact be modified in response to congestion or other information gathered as the tour progresses. The product of the model is essentially an itinerary of what activities, when, where, and in what order they will be engaged in by an individual. Trip tours are not developed within this framework. The model is also founded on the concept of *satisficing* rather than optimization. In other words, the process assumes that all information is either not known or considered to optimize a trip when an individual goes through the decision making process. The model has been internally validated (i.e., it successfully replicates sampled data), however, its use has not been extended to policy analysis. For each activity to be considered, the following information is assumed known: possible location, number of times the activity can be undertaken per day, time slots for the activities at each location, duration of the activity, priority of the activity, and the last time it was performed. This level of detail severely restricts the practicality of the model.

The Activity-Mobility Simulator (AMOS) model is a more recent model currently being developed to evaluate specific travel demand measures for the Metropolitan Washington Council of Governments (MWCOG) (RDC Inc., 1995). The undertaking is partially sponsored by the Travel Model Improvement Program (TMIP) sponsored by the U.S. Federal Highway Administration. Using a technique similar to CARLA, AMOS transforms a baseline activity schedule of an individual based on adaptation options (using a neural network) for a policy being evaluated. Revealed preference data is required to drive the model. In this respect, AMOS can be thought of as a switching or *change* model. The model continues to search for alternatives until a satisficing rule is met. A satisficing rule is usually a heuristically defined minimum threshold of utility required before an alternative is accepted. The model is driven by a micro-simulator that controls many of the layers of constraints (e.g., time, cost, etc.). The model is developed as a policy-specific evaluation tool. Six specific TDM techniques proposed by the MWCOG were incorporated into the model development. Stated response results are required as input to test specific policies.

The AMOS framework consists of four main components:

(1) The baseline activity-travel analyser reads individual trip records from household travel diaries. It identifies key characteristics (e.g., number of stops on way to/from work, mode, etc.) which are used to constrain output in subsequent modules.

(2) The TDM Response Option Generator uses a neural network trained on the results of revealed preference and/or stated preference data to produce the most likely TDM response option of an individual. Inputs include socio-economic characteristics of both household and individual associated with the travel diary from (1).

(3) The Activity Travel Pattern Modifier generates (using a complex re-sequencing and rescheduling algorithm) feasible alternative activity patterns that may be adopted depending on the TDM response. It uses sets of heuristic rules and constraints to generate the alternative patterns. Constraints include spatio-temporal, physiological, coupling, household role, modal, activity-specific, and value of time. Separate algorithms are used for each TDM response.

(4) The Evaluation Module evaluates the utility of alternative activity patterns to determine whether a sufficient solution exists, or whether the search should continue.

The AMOS framework incorporates many components of the methodology identified in Figure 1.5. AMOS does, however, rely on household travel diaries as a fundamental input to the model. In its current state, AMOS is extremely reliant on detailed input data. It will not allow analysis of individuals without associated trip and stated-response information (i.e., no mechanism allows assignment of baseline, or typical, activity patterns to individuals based on their socio-demographic characteristics).

The Los Alamos National Laboratory is currently developing the Transportation Analysis and Simulation System (TRANSIMS) (Smith *et al*, 1995). This development of TRANSIMS is an effort toward the operationalization of a more comprehensive planning tool. It consists of four main interconnected components including:

(1) A module that develops synthetic populations with household activity itineraries.

(2) A router that converts the activity list to a transportation network satisfying individual preferences and goals.

(3) A micro-simulator (similar to traffic models like TRAF-NETSIM) to evaluate network operations.

(4) A component that assesses environmental impacts on factors such as air quality and noise pollution.

Each TRANSIMS module is at a different stage of development; however, preliminary results indicate that the computational and data requirements of such a comprehensive model will be enormous (computer storage requirements are estimated in the order of tera-bytes). While the microsimulation of network operations is fairly well developed, the module for the generation of household activity itineraries is not well advanced at this point. The objective of the model will be to provide a tool capable of analysing an entire MPO. A primary reason for the development of TRANSIMS is to develop a tool capable of quantifying the environmental implications associated with TDM policies.

The TRANSIMS methods deal with discrete behavioural units including households, residents, vehicles, and loads of freight. The regional microsimulation executes the individual trips on the transportation network and predicts the performance of each vehicle. Air quality analysis is a fundamental objective of the proposed system. The Dallas-Forth Worth area has been selected as a test case for model development.

2.2.3 Activity-Based Modelling Issues

Activity-based model development efforts to date have been plagued by many constraints. It is of particular interest to this study that many of the previous efforts have relied on a baseline activity agenda that assumes that the commuter work trip tour is the primary set of activities for households. This approach seems to have spilled over from the traditional four-stage technique where the weekday peak hour is the fundamental concern. Such a foundation does not serve the study of travel behaviour of specific interest groups (e.g., elderly, newly licensed, etc.).

Current efforts in the United States and abroad are concentrating on all-encompassing models that are primarily of interest to MPO's. Such large scale developments require enormous investments in a methodology that is still essentially unproven. To date, there have been only a few cases were subcomponents of the activity-based approach have been operationalized. The complexity of many of the individual components is daunting to many planners. The use of the technique to allow planners to gain a better understanding of the travel behaviour of specific user groups seems to have been avoided.

Validation of the techniques remains an unexplored area. The fundamental problem is that one cannot validate a forecast. Before and after data bracketing policy implementation is necessary before a methodology can be evaluated. Internal validation may be achieved by comparing model output against unused sample data; however, this only quantifies the model's ability to replicate the existing system rather than test its capabilities for policy evaluation.

2.3 Studies of Elderly Travel Behaviour

A number of previous studies have examined different aspects related to mobility issues among the elderly. They can be broadly categorized as those dealing with demand for public transportation services or those characterizing travel patterns. In general, most studies have been deficient for one or more of the following reasons:

(1) Very small sample sizes.
(2) Aggregation of all elderly into a single group.
(3) Aggregation of the elderly with the disabled.
(4) Improper or weak theoretical basis for model or projections (including lack of behavioural realism).

The relatively small sample sizes supporting past analytical studies have been either the result of the data being culled from surveys covering the general population or simply the result of the research efforts being small in scope at the onset.

Most of the studies (detailed below) have aggregated all of the elderly into a single group with assumed homogenous characteristics even though it is well known that this sub-population is extremely diverse in terms of mobility and travel behaviour. Some studies have even amalgamated the elderly with the disabled to evaluate the need for specialized transportation services. Finally, any predictive models that have been developed are relatively simplistic in form (trip rates or linear regressions) and cannot be considered behavioural in nature.

Few studies have tried to derive a general travel demand and mode choice model specifically for the elderly. Studies have been as simplistic as those which have merely developed trip generation rates (Comsis Corp., 1986). An early attempt was undertaken that examined the relationship between trip-making and independent variables (Hartgen and Howe, 1977). Disaggregate linear regression models were developed based on a sample size of only 130 elderly to predict trip demand and mode split. Their findings highlighted the difficulties encountered when dealing with such a heterogeneous group indicating that a more robust approach is necessary.

A small study undertaken by Miller (1976) was an early attempt to quantify the *latent* (unmet) travel demand among the elderly and disabled using a small sample of stated preference data. The approach disaggregated the study group according to socio-demographic and mobility characteristics. Although the categorical analysis was limited, it did illustrate that for different groups, barriers to transportation significantly restrict access to discretionary activities.

Most of the research that has dealt with the quantification of elderly travel demand has tried to evaluate the desire for, and impedances to rural (Burkhardt, 1978; Wallace, 1983; Sperling and Goralka, 1988; SG Associates, 1995; Aoshima *et al.* 1992; Kihl *et al.* 1990) and urban (Lago and Burkhardt, 1980; Parolin, 1988; Rutherford and Latteman, 1988) public transportation services. While these studies fill a practical need, they fall short of providing a comprehensive tool capable of describing and analysing travel behaviour characteristics, given any number of circumstances, among the aged.

Most of the travel demand models that have been constructed try to predict trip-making as a function of public transportation service attributes (e.g., fares, headways, frequency, coverage, etc.) and socio-economic characteristics of users. Work undertaken by Lago and Burkhardt (1980) developed aggregate demand models for the elderly (as a homogenous group) using regression analysis on ridership data from transit companies. Less technical approaches have also been undertaken. For example, Sperling and Gorlka (1988) simply interviewed elderly riders to develop a profile of existing users so that potential areas for expansion could be developed.

A recent effort undertaken by SG Associates (1995) developed a "turnkey" approach for use in estimating the demand for rural public transportation services (both new and enhancements to existing services). A workbook was developed to aid local planners through the process. However, the basis for the demand models are relatively straightforward regression models (for demand) and logit models (for mode choice). Again, models with such a narrow focus do little to allow planners to develop a better understanding of general travel behaviour.

Several studies have tried to document the general travel characteristics and patterns of the elderly group (Rosenbloom, 1995; Comsis Corp., 1986; Institute of Transportation Engineers, 1994). Two of these reports (ITE and Rosenbloom) have developed general travel behaviour characteristics using the 1990 Nationwide Personal Transportation Study (NPTS) conducted in the United States. The survey included responses from more than 48,000 persons, roughly 12% of which were from those over 65 years of age. Both studies present fairly coarse results including statistics on average daily trips, miles of travel, trip length, and vehicle occupancy. Rosenbloom's study linked socio-demographic changes to evolving travel patterns; however, the time interval only encompassed a seven-year period. While the information presented in these reports is interesting in a general sense, it is devoid of behavioural relationships and is only an examination of broad characteristics. For example, where it is shown that there is an increase in the trip rates among the elderly, the underlying reasons (including whether it is out of necessity or by choice) are not apparent. This type of analysis does little to enhance a planner's ability to consider the impacts of fundamental changes to the transportation system on the elderly.

More generalised evaluations of elderly travel needs have been undertaken. For example, Wolfe and Miller (1983) describe an approach that disaggregates the elderly into seven lifestyle groups and future impacts (including transportation, organizational, and service-related innovations) were heuristically evaluated for each category. The lifestyle groups were merely defined "judgementally, subject to the requirement that they be specifically transportation related and that they be invariant with time......" The groups segregated those who were:

(1) Institutionalized.
(2) Sheltered or in group housing.
(3) Handicapped.
(4) Independent with their own automobile.
(5) Independent without an automobile.
(6) Dependent with access to an automobile.
(7) Dependent without access to an automobile.

While this approach may be useful for broad, long-range planning it is too subjective and coarse to allow for a detailed understanding of the elderly's travel behaviours and needs.

Rutherford and Latteman (1988) describe an expert panel technique used in Seattle to develop and evaluate future scenarios which were influenced by external factors such as the economy, technologies, demographics, and potential policies. The panel of experts consisted of members with knowledge of economics demographics, social sciences, development, law, trade, and business. A matrix of possible scenarios which varied economic growth rates and energy costs were considered. Transportation impacts on the travelling public (including the elderly as a specific group) were considered and different long-term mitigative planning strategies developed for each scenario.

An example of a very specific study addressing the travel needs of the elderly was produced by Marottoli and Ostfeld (1993). They examined the linkages between driving cessation and different socioeconomic factors. Primary independent predictors were found to be either physical attributes (diseases affecting neuromuscular and visual function, increased disability, or decreased physical activity) or social characteristics (economic cost and retirement).

While there have been a number of previous studies that have targeted the elderly as a group, most of the work has been either too specific or superficial to provide an in-depth understanding of the travel needs and behaviour of the aged. None of the previous approaches provide an appropriate framework to allow planners to evaluate the impacts on the elderly associated with changes in policy, social programs, or in infrastructure.

The ability to use the model to forecast trip-making of future elderly populations will be highly dependent on the ability to forecast the variables upon which dissaggregation is based. Some researchers believe, or make the assumption, that travel behaviour within each category will remain relatively stable temporally, and that future generations of the elderly will merely occupy different proportions of the same categories. This is probably a simplistic view of evolving cohort changes for which there is, unfortunately, little empirical evidence.

2.4 Microsimulation

The use of microsimulation for travel analysis is gaining support as its many advantages become better understood. Microsimulation refers to an explicit analytical process that aims to replicate a real world system so that modifications to the system can be tested and evaluated. The term *micro* refers to the aspect that discrete objects or entities (rather than aggregations) are the primary units of analysis. For example, management scientists often simulate the processing of production units (widgets) through a factory or assembly line. The field of transportation has come to utilize microsimulation to evaluate the movement of vehicles or units of freight through a network.

Microsimulation departs from traditional analyses in that forecasts are not reliant on deterministic relationships. Instead, microsimulation tries to replicate the system being modelled and tracks performance of individual units as they progress through time or a series of processes. For example, one could be interested in tracking an individual through the course of a day, week, year, or lifetime and examine different processes such as mode choice, car buying, home relocation, etc. The individual response to processes can be governed by a series of rules, algorithms, models, or stochastically with a Monte Carlo technique. The potential usefulness for microsimulation in transport policy analysis has been well documented, however, there has only been a handful of applications to date (Arrow, 1980; Orcut *et al.* 1980; Law and Kelton, 1991).

Increased demand for models using microsimulation as a platform stems from (Goulias and Kitamura, 1993):

(1) A need to assess policy impacts at a micro level (for example, adverse impacts on specific groups tend to get masked with traditional analyses).
(2) A desire to include variability among individual decision-making units with common attributes (therefore more realistically representing the responses of individuals).
(3) Potential for increased accuracy through direct observation of individual units.
(4) Provision of rich statistical output.
(5) Explicit inclusion of a temporal dimension.

With the trend toward increasingly disaggregate analyses, microsimulation provides a natural framework to process either individuals or households. A bottom-up approach results whereby individual behaviour is projected and then aggregated with other individuals to produce zonal or system-wide response. As Goulias and Kitamura (1993) note, "microsimulation follows the basic tenet of microeconomics -a complex entity composed of many constituent components can best be explained and predicted through an analysis of its constituent parts."

Individual simulation units are typically processed through time which provides a dimension not readily available through traditional methodologies. Previous techniques have been *temporally cross-sectional* which, as Davies (1987) notes, restricts analyses from examining cohort effects, fail to resolve ambiguities in causalities, exaggerate the behavioural effect of policy changes, and cannot provide methods to consider observable or unobservable omitted variables. Disadvantages of using microsimulation are that data requirements are often onerous and model development can be relatively complex.

With the emergence of relatively powerful desktop computing, microsimulation has only recently become a tool accessible to most analysts. An example of its use in the transportation field is the TRAF-NETSIM model which is an alternative technique now available to analyse the operational characteristics of traffic on road networks. Each vehicle is simulated as it flows through time and space and responds to changes in the system environment. Individual vehicle results are then combined at different levels of aggregation. Policy analysis and travel demand behaviour is proposed to be modelled in much the same way except individual vehicles are replaced with individual trip makers. Most past or proposed applications of microsimulation for travel analysis have focussed on using it to develop dynamic (progression through time) models. Limited use has been made of microsimulation to stochastically develop synthetic populations for use in other demand modules.

Goulias and Kitamura (1992) have developed a prototype model using econometric models incorporated into a microsimulation system designed to predict trip generations and mode split based on the Dutch National Mobility Panel Data. The model is called the Microanalytic Integrated Demographic Accounting System (MIDAS). The model relies on a socio-demographic component that aims to recreate the progression through life-cycle changes (drivers' license, marriage, children, home ownership, unemployment, divorce, retirement, etc.) thereby internally generating variables such as income, employment, drivers' license holding, and education for use in the second module of the simulation system. The second module, the mobility component, uses the outputs of the first component to generate car ownership and mobility attributes (trip generation, mode split, etc.). Such an approach can only be facilitated with the use of microsimulation as a platform. A recent update of the MIDAS system is incorporated in the MIDAS-USA-Version I (MUVI) system that has been calibrated to U.S. data (Chung and Goulias, 1997).

Mackett (1990) developed a temporal model of household evolution named Micro-Analytical Simulation of Transport, Employment and Residence (MASTER). The model essentially ages households within a study area through time periods. During each time advance, households readjust their attributes if appropriate. For example, young people become economically active if they become employed, households may move if their incomes increase, young families have children, etc. Transport processes considered include: obtaining a driver's license, car ownership, car availability, and mode choice for work trips. The model has been used to test the elasticity of increasing bus fares. Many of the internal decision rules and processes have been simplified because of a lack of data or understanding of the underlying mechanism. The model employs Monte Carlo simulation to step sequentially through a series of processes (e.g., choose mode, buy a car, form a household, etc.). The complexity of the model stems from the sequencing of events, household interactions, and supply side constraints (e.g., homes and jobs). Supply side constraints are included by distinguishing between the decision to enter a process and the satisfactory outcome of the process. If the process does not result in a suitable outcome, then the state of the individual will remain unchanged. For example, if a job opportunity does not exist, then mobility will not increase.

The SMASH model (previously described in section 3.2, a pre-trip activity scheduling model) is another example of the use microsimulation. In using microsimulation as a platform, SMASH incorporates computational process models to describe the internal decision rules. The TRANSIMS, AMOS, SMART and ORIENT models, previously discussed, all use microsimulation as the technique to drive their processes. Despite using microsimulation as a common system, each model can use different internal techniques such as neural networks, stochastic assignment, and algorithms to formulate decision rules.

In summary, microsimulation is a computing framework that provides an opportunity to undertake analyses which are fundamentally different from traditional models. Its main advantage is the ability to simultaneously process individual units and track their response to different stimuli as they progress through time and space. Microsimulation provides a natural foundation for activity-based frameworks given the inherent level of disaggregation, layers of constraints, and many factors that are inherently stochastic.

2.5 Categorical Stratification

An underlying premise of the proposed research is that within the relatively heterogeneous elderly population, there exists homogeneous subgroups with similar lifestyles, common activity patterns, and corresponding travel needs and behaviour. This section discusses some previous efforts and methodologies that have been undertaken to explore the categorical stratification of trip-makers in an effort to understand travel behaviour.

2.5.1 Previous Stratification Studies of the Elderly

In the past, there has been a tendency for analyses to rely on age as the only basis for stratification of the general population. Nelson and Dannefer (1992) point out that the

> ".....recognition of heterogeneity is important because there has been a tendency to rely on averages, stereotyping, and age norms inherent in an age stratification system. These norms have, in turn, often lead to guide social policies for older people."

Results of studies by Light *et al* (1996) show that the heterogeneity in a birth cohort will actually increase over one's life course on a broad range of personal characteristics including income, education, health, cognitive ability, and personality. The result is that the aged are highly diverse and perhaps the most heterogeneous of any age strata. Despite this characteristic, much of the literature from the social sciences (particularly between geographers and gerontologists) reveals a striking dichotomy in this population. Clark and Davies (1990) explain that numerous studies address the increasing problems of *economic survival* of the aged while others focus on the growing population of the *affluent* elderly. However, they contend that much of the literature propagating this dichotomy is "descriptive and interpretive, rather than analytical and statistical."

Fields of study apart from travel modelling have developed lifestyle categories in trying to establish a better comprehension of the behaviour among group members. The *behaviour* that is trying to be understood or made predictable typically dictates the basis of stratification. For example, demographers tend to use socioeconomic variables descriptive of one's current position in the life-cycle to forecast future membership within each stratum (Uhlenberg, 1996). Health scientists have stratified the aged based on their health needs or physical limitations to gain a better understanding of the risk factors that contribute to diminished functioning (House and Lepkowski, 1994).

Disciplines such as geography and marketing have developed geographic-based lifestyle strata of the aged. For example, Wachs (1979) used factor analysis to extract seven lifestyle dimensions for geographic neighbourhoods within Los Angeles. The geographic basis was necessary to allow predictions of the effect of proposed public transportation policies targeted to distinct areas within the city. Marketers widely use a database (PRIZM by Claritos Inc.) which classifies every United States Zip Code into one of 40 lifestyle categories (Englis and Solomon, 1995). Lifestyle categories are constructed on the basis of purchase behaviour of consumers and, to a lesser extent, on personality traits such as opinions, attitudes, and personality.

Previous transportation related studies have developed different bases for the segmentation of the general population. Much of the work has focussed on relatively general socioeconomic attributes such as income, employment, household size, sex, and age. Wermuth (1982) found that

> "...the obligatory activity levels (work, education/training) can be attributed almost exclusively to person-specific characteristics, and that 70% of the variance for private activities of individuals can be attributed to personal characteristics, between 15-30% to household characteristics, and only up to 4% to locational characteristics."

Given the close relationship between personal characteristics and activity engagement, the use of categorical stratification is justified for the overall population. A more refined examination of the elderly may yield similarly useful results.

Kitamura (1988a) notes that a number of studies "support the conjecture that household structure significantly influences the activity and travel patterns of household members, and they point to complex interaction between household structure and gender." To date, household size has often served as a proxy variable for the actual structure of the household. The structure may prove to be an important predictor of mobility among the elderly as some individuals rely on partners or co-habitants for their transportation needs.

Nicolaidis *et al* (1977) suggest that the segmentation of the study population into groups should be evaluated based on the following criteria:

(1) Measurability: the variables upon which segmentation is based must be relatively easy and cost effective to obtain.

(2) Statistical robustness: categories should be statistically different from one another. Inter-segment variation should be greater than intra-segment variation.

(3) Substantiality: each segment should be large enough in size to account for a significant proportion of the population under study.

(4) Relation to travel behaviour: the segment should account for as large a proportion of the variance in activity patterns as possible.

(5) Relation to planning of service options: if particular transportation service packages serve consumers having very different social or economic characteristics, a segmentation base that defines consumer groups compatible with service options would be more useful than a base that does not. Similarly, if promotional activities are targeted at consumers having certain preferences, perceptions, and desires, a segmentation procedure that identifies those groups would be more useful than one that does not. For example, if the intended use of the model were to evaluate changes in transit policies, segmentation may be formed based on transit usage or auto availability.

The first attribute, measurability, can be associated with variables that are abstract enough that simple observation or measurement is insufficient. For example, Prevedouros (1992) found relationships between trip-making and personality characteristics such as social introversion or extroversion, affinity for material possessions, and affinity for suburban living. While the inclusion of such personality attributes would help explain some variance, the difficulties associated with measuring and collecting this information precludes their usefulness. For practical reasons, one is often restricted to stratify on the basis of variables already contained in an existing data set.

Life-cycle stages and lifestyles have also been studied as a basis for segmentation. Although results have been mixed, Clarke *et al* (1981) have found some success in explaining differences between groups based on stage in the life-cycle. Using weekly activity diaries, typical activity patterns were identified for each of eight life-cycle groups (which they predefined). Most life-cycle segmentation efforts have shown that the presence of children within the family household has a profound influence on trip-making. The elderly have normally been aggregated as a single life-cycle group despite the inherent heterogeneity within this group. This study will be the first to quantitatively (rather than heuristically) stratify the elderly group into lifestyles.

An interesting finding by Clarke *et al* (1981) was that 80 percent of all trip tours among the retired were simple one-stop circuits. This value was by far the largest among all life-cycle groups indicating the propensity for complex of trip-making given the presence of children and obligatory work commitments.

The concept of using life*style* as the basis of categorizing individuals has been evaluated in a few previous studies but has recently gained interest in light of activity-based modelling. In fact, Salomon and Ben Akiva (1982) found that life*style* discrimination forms a better basis for stratification than either income or life-cycle/occupation bases. They define lifestyles as "the behavioural pattern that results from three major life decisions: the decision to form a household, the decision to participate in the labour force, and the orientation toward leisure." Reichman (1977) identifies four lifestyle characteristics that affect travel behaviour including economic resources, social engagement, role differentiation, and time control.

Principio and Pas (1997) developed seven distinct lifestyle groups among the general population based on time-use information. They found that nearly 80 percent of the variation in time-use was captured within the seven groups implying that there are systematic patterns of activity participation among the groups. Note that they assumed that lifestyle manifests itself in time-use patterns.

Kitamura (1988b) notes that a fundamental difficulty of using lifestyle as a framework is that it involves *values* and *orientations* that are not measured in typical transportation surveys. However, he does go on to indicate that variables such as life-cycle stage, age, employment, sex, income, car ownership, and license holding have been theorized to reveal lifestyle characteristics. It is interesting that he highlights car ownership and license holding as *conscious* lifestyle choices. While this may be appropriate among the population overall, it may not be a choice among the aged. While many of the established lifestyle definitions may be applied relatively well to the population in general, most may be too broad to encompass the elderly as a subpopulation. The elderly are often faced with unique mobility constraints which must be considered when defining lifestyle categories. The household structures common among the elderly, and financial or physical limitations are but some characteristics that may be found to profoundly affect activity engagement outside the home.

2.5.2 Methods of Stratification

While there is no best method to identify the basis for segmentation, the general approaches are to define them *a priori* (in part, based on the above criteria, and according to the end use of the model), or analytically. The most common quantitative approaches employed for stratification include regression, discriminant analysis techniques, and cluster analyses. Analytical techniques may stratify individuals on the basis of observed behaviour such as mode choice, frequency of trip-making, or activity patterns (e.g., time spent in work, personal maintenance, or discretionary activities). The observed behaviours can be used as the dependent variable upon which segmentation is based. Observed travel patterns are typically clustered using analytical techniques and then common characteristics (or arrays of socio-demographic characteristics) of group members identified. In contrast, a number of efforts have grouped trip-makers based on independent variables such as socio-demographics or time-use data, and then proceeded to explore the differences in travel behaviour among the groups. Time budget studies have widely taken the approach to predefine population subgroups and then examine the variations in time-use patterns between groups.

Regression analyses allow independent variables to be identified which are correlated with the dependent variable. The independent variables that explain a significant portion of the variance of the dependent variable can provide a basis, or dimension, for segregation. However, such an approach falls short of identifying subgroups of observations, defined multi-dimensionally, with common relationships or characteristics. Even the best groupings of a given single variable would have to be determined by 'trial and error' with the objective of minimizing the standard deviation of the observations within the group. To consider multiple variables compounds the difficulty of determining appropriate categories.

The area of discriminant function analysis deals with the problem of determining whether it is possible to separate different groups on the basis of the available measured attributes. If there are statistically significant differences between linear functions formed from the measured attributes for each group, then classifications of further observations whose group membership is unknown can be made. The method depends on group membership being either predefined or known for sample data. Given this prerequisite, the technique cannot be used to facilitate the identification of elderly lifestyle groups. Once the lifestyles are delineated, the technique could, however, be used to assign a person to an appropriate group given the proper attribute measurements.

The term *cluster analysis* is, in fact, a generic name for a variety of mathematical techniques that can be used to organize objects with similar attributes into groups or clusters. While many previous efforts have developed classifications heuristically, cluster analysis permits a more objective and mathematically sound basis for segregation.

Although individual steps of cluster analyses can be carried out by employing different techniques, the overall framework consistently involves the following steps (Romesburg, 1984):

(1) Develop a matrix of case information .[1]

(2) Standardize the data within the matrix.

---

1 Normally the *objects* to be clustered are set out as the columns, while their corresponding attributes, being used as the basis for the establishment of clusters, are the rows.

(3) Compute 'resemblance' coefficients between all pairs of objects.

(4) Apply a clustering method to the data set (often resulting in a tree or dendrogram).

Depending on the type of data (e.g., nominal/categorical, ordinal, interval/ratio) within the matrix, and the specific approach being employed, steps 2 through 4 can use different techniques. It is necessary to standardize the data so that attribute variables with large units do not over contribute to the clustering that occurs. For example, if income and age are to be included as object attributes, the absolute difference in the variable sizes would tend to skew the formation of clusters. The most common techniques are to either standardize the data to a mean of 0 and a standard deviation of 1, or convert the values into proportions.

Resemblance coefficients essentially reflect the 'spatial closeness' of the individual data points. Euclidean distances are often developed for quantitative data points. They are simply calculated as the geometric distance between individual points or clusters based on their Cartesian coordinates. The number of coordinates, or dimensions, which describe a data point's location will depend on the number of attributes being considered. Other resemblance coefficients including correlation coefficients can be employed depending on specific peculiarities of the data being analysed.

The most commonly used approaches to cluster the data (step 4) are the *agglomerative hierarchical* methods. These approaches systematically form larger and larger clusters until ultimately all cases belong to a single cluster. The most commonly used approach is the Unweighted Pair-Group Method using Arithmetic Averages (UPGMA). This approach essentially starts with each individual data point belonging to its own group. Individual pairs of data points are then sequentially clustered together (based on the strength of their resemblance coefficients) until all data points belong to a single stratum.

A disadvantage of the UPGMA approach is that it can be very cumbersome and require a huge amount of computing power for matrices that have a large number (approximately greater than 200) of data points. The *K-means* approach is one technique that can be used to overcome this issue. The K-means method only develops a solution for a predefined number of clusters as specified by the user so it is not considered a hierarchical approach. The initial (or starting) cluster centres are developed either by clustering a random sample of the data, or by heuristically identifying the clusters. As a result, the optimal solution is not automatically assured. Several transportation studies have utilized the K-means approach to identify distinct markets or groups of users including Salomon and Ben Akiva (1982) who developed five lifestyle groups based on socio-demographic variables in pursuit of mode choice models, Hanson and Huff (1986) who isolated clusters of trip-making based on the percent of trips made within distinct categories of activities, and Nicolaidis *et al* (1977) who segregated trip-makers into groups based on demographic and attitudinal variables.

Ward's minimum variance clustering method is another technique that has been employed in a transportation demand context. It starts with a fixed number of clusters and hierarchically collapses the data until a single cluster remains. Data points are joined into non-overlapping clusters based on the merger which will yield the smallest increase in an index, *E*, called a sum-of-squares index, or variance given by the following equation:

$$WSS_G = \sum_{g=1}^{G} \sum_{i=1}^{N_g} \sum_{l=1}^{L} (X_{ilg} - \overline{X}_{lg})^2 \qquad [2.1]$$

where,

WSS_G	=	within-group sum of squares for G groups
X_{ilg}	=	location on dimension *l* of observations in group g
$\overline{X}_{lg}$	=	mean location on dimension *l* of observations in group g
N_g	=	number of observations in group g
G	=	number of groups
L	=	number of dimensions in the real-space configuration

By minimizing the within-group sum-of-squares, the algorithm attempts to maximize the between group (or explained) sum of squares. In effect the variance (or information) accounted for by the classification groups is maximized. A disadvantage of the technique is that the resemblance coefficient cannot be chosen (it must be *E*). This, in turn, restricts the type of data which can be included in the analysis (e.g., qualitative data cannot be directly incorporated). Furthermore, it has been shown that this technique does not necessarily yield the optimal solutions (because once a data point is joined to a cluster, it cannot be reassigned to a different cluster at a later step). Examples of applications of Ward's method in the travel demand area include Principio and Pas (1997) who recently developed seven distinct lifestyle groups based on time-use data, and an earlier effort by Pas (1982) who developed clusters of activity patterns.

Once the clusters have been defined, it is often necessary to classify new objects as a member of one of the groups. This is known as *identification*. Although there are a number of discriminant function analyses that deal with the issue of identifying group membership of objects based on their attributes (e.g., Mahalanobis distances or canonical discriminant functions (Manly, 1986)), it is often as effective to employ steps which are consistent with those that were used to actually build the clusters. For example, resemblance coefficients are calculated between the unclassified object and each cluster. The object is then identified with the cluster to which it is most similar.

CHAPTER 3

RESEARCH APPROACH AND METHODOLOGY

The following sections describe the approach and methodology employed by the research study to address the deficiencies identified in Chapter 2. The primary tasks that were undertaken to complete the research include:

(1) Refinement of the overall framework of the proposed activity-based model.

(2) Detailed analyses of an activity-based survey to provide a detailed description of elderly activity engagement and subsequent travel behaviour.

(3) Identification of lifestyle groups among the elderly using the results of an activity-based survey. Clusters were formed on the basis of activity engagement patterns, socio-demographic variables, and travel behaviour.

(4) Four modules of the proposed activity-based framework (Figure 1.5) were developed including:

  (I) Categorization of Individuals.

  (ii) Engaged Activity Patterns.

  (iii) Adaptation Model.

  (iv) Trip Tours.

(5) Test runs of the activity-based model to reveal sensitivity and behavioural responsiveness.

The general approaches used to undertake the above tasks are described in subsequent chapter sections while the findings of analyses are presented in Chapters 5 through 7.

3.1 Data Requirements

A fundamental difficulty surrounding the development of an activity-based approach is the level of effort needed to obtain appropriately detailed data. Fortunately, a major data collection program in Oregon and Washington States has recently produced a significant amount of activity-based information. This data set was used as the basis for model development.

The *Oregon/Southwest Washington Household Activity and Travel Behaviour Survey* was initiated in April, 1994. When the data collection process was finished in January, 1995 nearly 12,000 households had been surveyed. The collaborative effort involved seven sponsors which are listed in Table 3.1 along with their respective metropolitan areas. A map that illustrates the geographic coverage is attached in Appendix A.

Table 3.1 Participants of the Oregon/Southwest Washington Survey

Sponsor	Metropolitan Area Covered
1. Mid-Willamette Valley Council of Governments	Salem/Keizer metropolitan area
2. Oregon Dept. of Transportation	*satellite* cities in Marion, Polk, and Yamhill Counties
3. Portland Metro	Portland metropolitan area (Clackamas, Multnomah, and Washington counties plus portions of Columbia and Yamhill counties)
4. Southwest Washington Regional	Vancouver (WA) metropolitan area
5. Transportation Council	Clark County
6. Lane Council of Governments	Eugene and Springfield (OR) metropolitan area. Lane County.
7. Rogue Valley Council of Governments	Medford (OR) metropolitan area. Jackson County.

Although the data sets for individual sponsors are in various stages of development at the time of writing, the City of Portland (usually referred to as Portland Metro, or METRO) has completed their database and made it available for the study. The computer files that contain the data have been available to the public since the fall of 1996 through one of the City's Internet websites [1]. Detailed descriptions of the survey methodology and its dimensions have been prepared by NuStats International (1995) and Cambridge Systematics (1996).

The information collected by the survey included socio-demographic, time-use (activity), travel, and stated preference data. Households were recruited and the information solicited from members for a two-day period. Table 3.2 summarizes the dimensions of the METRO data set. Note that records for those respondents whose age is unknown were removed from the base data set.

Table 3.2: Portland METRO Activity Data Set Dimensions

Variable	**Total (all ages)**	**Total (65 yrs. old)**
persons surveyed	9,866	1,150
person-days of information	19,732	2,300
households	4,451	701
individual activities	126,892	16,843
individual activities involving travel	70,630	6,599

The data set consists of individual files that contain information broadly categorized as activity, household, person, and vehicle characteristics. Table 3.3 identifies some of the variables contained within each computer file. These file structures are consistent across each survey undertaken by the seven sponsors. A more comprehensive listing of the data items collected as well as example data are presented in Appendix B.

All data files are available in either ASCII or dBase IV format. Most analyses were undertaken using standard dBase IV functions; however, the files were easily converted into a format appropriate for use in the statistical package SPSS.

1 Internet URL address is: ftp://ftp.metro.dst.or.us./sys/ftp/planning/tf/pub/

Table 3.3: Portland Metro Activity Data Set File Structure

File Description	Key Variables			
Activity 1 File*	activity	spatial/temporal details of activity		travel mode
	activity pattern	auto availability	travel costs	transit details
	travel group size	driver/pax	parking details	
Activity 2 File	refined spatial details linked to Activity 1 File			
Household File	geographic survey stratum	size	# of vehicles	income
	residence details	activity day	proximity to LRT	
Person File	age/gender	ethnicity	household role	language
	licensed	student details	employment details	disability
Vehicle File	year/make/model	type	miles during survey	

* Only those activities that lasted at least 30 minutes or required travel were recorded.

While the Portland Metro's activity data set provided the foundation for the development of the base travel model, stated preference data was also required to test the model's sensitivity to policy changes. In concert with the activity survey, a stated preference survey was also conducted that solicited information on:

(1) Road pricing.
(2) Housing location choice.
(3) Auto acquisition.

This study made use of the road pricing survey results. The survey presented different scenarios of proposed increases in travel cost (through tolls, gas tax, and parking) and congestion levels (measured on the basis of travel time) for different modes and times of day. The respondent was asked to select the scenario they would most likely use for specific trips. Separate survey techniques were used to solicit information for trip-making to and from the workplace or for trips not related to work. For non-commute trips, respondents were reminded of a specific trip they had recorded for the activity survey and were then asked how they would make the same trip (if at all) given eight proposed pricing scenarios. A total of 2,544 responses are contained in the data set, 512 of which were completed by those 65 years of age or older. This is normally referred to as a stated *adaptation* survey. Possible adaptive behaviours recorded by the survey included:

(1) Modal change (drive alone, driven/carpool, public transit, bicycle, walk).
(2) Make trip less often.
(3) Combine trip with other trips.
(4) Make trip at different time of day.
(5) Look for similar destination closer to home.
(6) Do activity at home.
(7) Not make a trip at all.
(8) None of the above (i.e., different or no adaptation).

If a proposed policy is expected to have a more positive influence on mobility, then responses opposite of those listed above might be expected. The intent of the research was not to provide profound insight into the effect of these specific pricing scenarios, rather to test the usefulness of the proposed framework for these types of analyses.

3.2 Activity-Based Model Development

An activity-based model was developed using microsimulation as the platform which incorporated the Portland Metro activity data set. The General Purpose Simulation Software™ (GPSS/H) package was used to construct the simulation model. There are several microsimulation software packages available, however, GPSS/H was chosen given its availability and the author's familiarity with it.

Figure 3.1 presents an overview of the model structure. The model processes are described in more detail in subsequent sections. The modules included in the framework relate directly to four of those described in Figure 1.5 including: Categorization of Individuals, Engaged Activity Patterns, Trip Tours, and Modified Trip Tours. Again, given the scope of this study the complexity of some modules and linkages identified in Figure 1.5 could not be addressed. Some deficiencies outlined in Chapter 2 regarding current modelling systems are addressed by the proposed framework including:

(1) Practical demonstration of a simplified activity-based model.
(2) Categorization of individuals will reduce the amount and detail of data required for the model (i.e., lifestyle segmentation will homogenate activity and subsequent travel behaviour patterns).

(3) Application to a specific user group rather than the typical commuter focus.

(4) Inclusion of microsimulation as a platform for model development.

(5) Construction and operationalization of a framework that can be expanded to include more complex behavioural processes.

(6) Ability to analyse the travel implications associated with adaptation responses.

One of the major disadvantages of the proposed framework is the omission of any scheduling constraints or optimization routines which could be used to more realistically assemble activity patterns and trip tours.

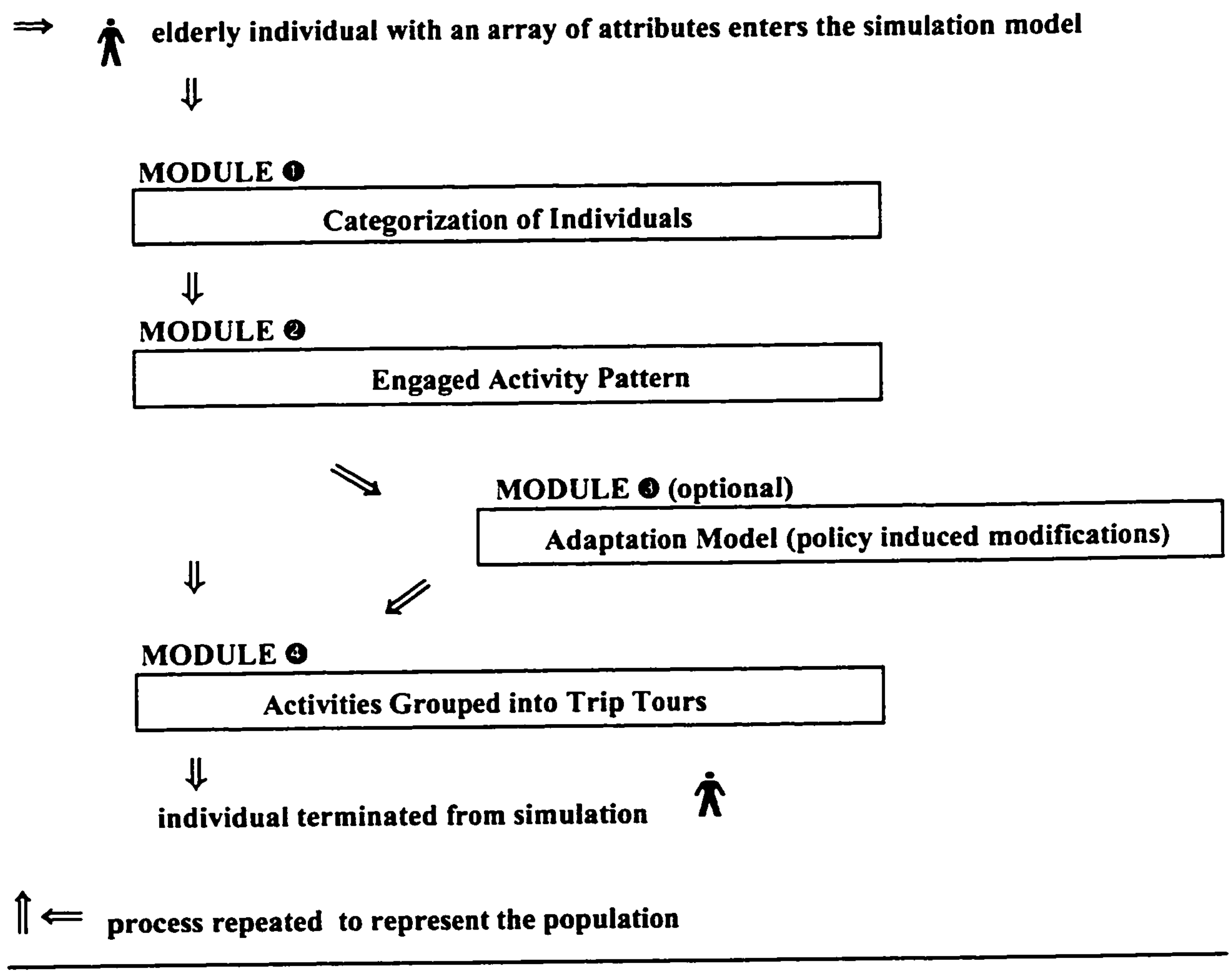

Figure 3.1: Activity-Based Model Flowchart

Figure 3.1 shows that the model framework processes individuals discretely until a set of daily trip tours (or chains) is developed based on the assigned activity itinerary. For the purposes of this study, a trip tour was considered as a string of activities that begins and ends at home. This is a definition that is consistent with several existing activity-based models. Studies concerned with commuter behaviour have often segregated trip tours into home-work, work-home, or work-work tours.

At the onset, individuals are assigned to one of several homogenous groups which, in essence, impart a form of categorical analysis into the model. Individual activities are stochastically assigned using empirical distributions (probabilities representing actual observations) in concert with heuristically set constraining rules. Finally, trip tours are developed by grouping the activities based on simplified linear relationships between the number of mandatory or discretionary activities and the resulting number of daily trip tours.

3.2.1 Module 1: Categorization of Individuals

The initial step in the proposed model was to stratify the heterogenous target group (the elderly) into a number of smaller, more homogenous, subpopulations. The intent was to establish groups that are distinct in terms of travel behaviour, travel resources and their reactions to change. The underlying premise is that the prediction of activity engagement (and hence travel behaviour) is facilitated by identifying homogenous groups who have similar travel patterns and similar responses to changes in the transportation system. A flow diagram of Module 1 is depicted in Figure 3.2 and the steps described in subsequent sections.

Cluster analysis was used to identify distinct lifestyle groups among the elderly. A by-product of this analysis is a better understanding of the relationships between time-use/activity engagement, socio-demographics, and travel behaviour. This is a significant contribution of the study.

Using the SPSS software, the Portland METRO data set was evaluated using cluster analysis to identify lifestyle groups. As previously noted, there was a total of 1,150 persons 65 years of age and older interviewed as part of the data set. A total of 16,843 activities has been inventoried for this age group, 6,599 of which required travel outside the home.

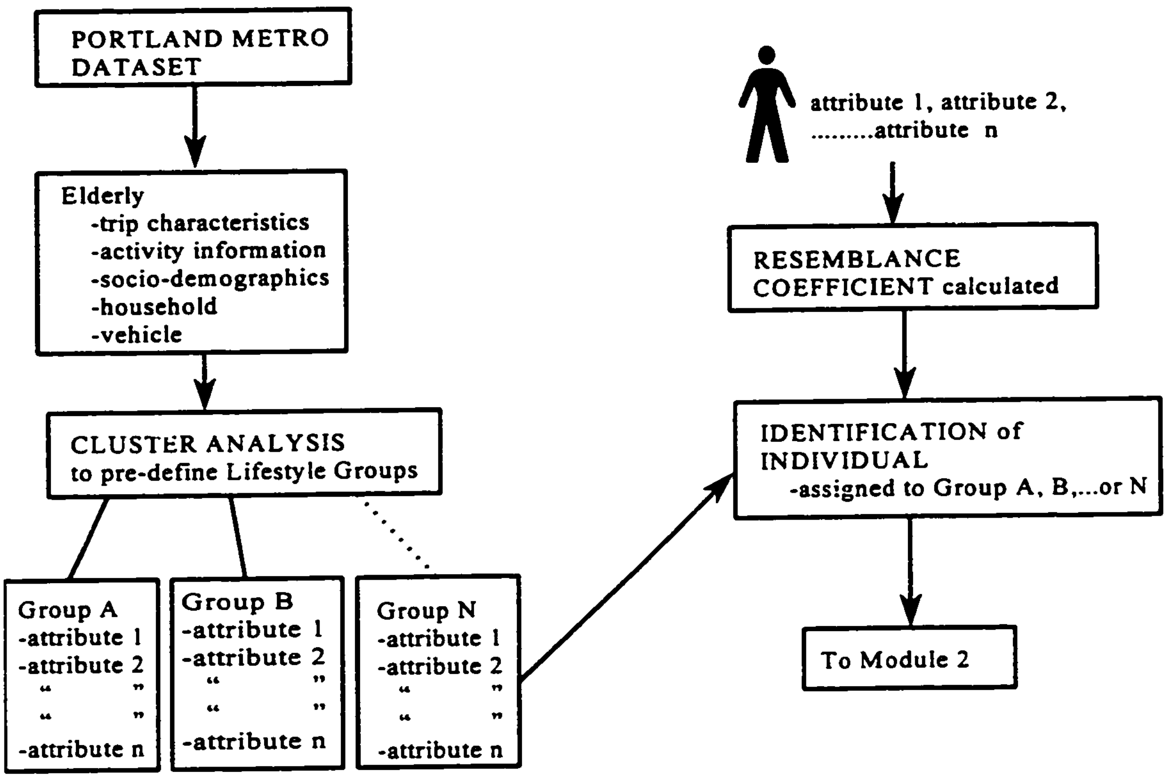

Figure 3.2: Module 1: Categorization of Individuals

Since there is no single clear means to define or characterize one's lifestyle, a three-pronged approach was employed to explore the relationships between lifestyle, activity-engagement, and travel behaviour. These approaches are presented in the following sections.

3.2.1.1 Activity-Engagement Dimensions

Lifestyle clusters were developed on the basis of *activity-engagement*. The analysis was undertaken at the person-level. The number of hours engaged in different classes of activities (over the two-day survey period) was used as the basis for lifestyle segregation. The data set recorded activities into one of 27 specific activities. The actual number of activity classes used for segregation into lifestyles included those involving subsistence (work, school), maintenance (shopping, banking, etc.), leisure (social, recreational), and other. Non-substitutable in-home activities (e.g., household cleaning, bathing, etc.) were excluded from consideration since they have no direct relationship with travel behaviour. These activity classifications are consistent with many time-use studies. In fact, Principio and Pas (1997) used a clustering technique to identify specific groups of activities that yielded similar groups to those employed. Principio and Pas used the percent time engaged in different classes of activities as the basis for the development of lifestyle groups. However, this approach could dilute the effect of those who are relatively overactive or inactive (a prevalent characteristic among the very old) since the *proportion* of time engaged in a specific class of activity does not reflect frequency of engagement.

K-means cluster analysis was utilized given the large matrix of information that needed to be segregated. The rows of the matrix represented the 1,150 elderly survey respondents, while the columns provided the daily amounts of time individuals participated in each of the activity classes. A random sample of 250 individuals drawn from the data set was initially cluster-analyzed using the UPMGA approach (a hierarchical method) so that the optimal number of clusters and initial cluster centres could be determined before all records were included in the K-means approach. Examination of the cluster tree, or dendrogram, produced using the UPMGA method facilitated the decision on the number of clusters that were included. A common strategy is to use a number of clusters that are well separated (in terms of resemblance coefficient, or the y-axis of the tree) from adjacent levels of clustering. Such a strategy minimizes the sensitivity to error of selecting an inappropriate number of clusters. When the final clusters were developed using K-means, the calculation of a within-group sum-of-squares provided a statistical measure of the 'information retention' achieved by grouping the records.

The cluster analyses yielded what are known as *polythetic classes* which permit differences on a few attributes if the average difference over the whole set of defining attributes is tolerably small. For example, one cluster may be defined by those who are affluent, hold a driver's license, own a single family dwelling, are married, and have no children living at home. Individual members of the cluster are permitted to deviate from some of the defining dimensions of the cluster (e.g., live in an apartment).

ANOVA was used to examine the variation in socio-demographic and travel behaviour attributes between each of the lifestyle groups identified through cluster analyses. This analysis provided insight into the characteristics that are significantly different between lifestyle groups. Frequency analyses were used to examine within group distributions of socio-demographic and travel behaviour attributes. Travel behaviour can be characterized by variables in the data set such as the number of trips, activities per trip, average duration, total travel time, mode, number of people in party, cost, and role (driver/passenger). These variables are contained in the Activity 1 file of the database. Socio-demographic variables such as age, gender, household role, employment, driver's license, and disability are contained in the Person File, while household size, income, and proximity to the light rail system are contained in the Household

File. Again, an underlying premise was that travel behaviour characteristics are relatively homogeneous within the groups and significantly different between the groups.

An important premise of the travel model is that members of common lifestyle groups are assumed to have similar responses to policy changes. Variations in stated adaptation responses generated from the Portland survey on road pricing were examined between the groups generated by the cluster analysis. ANOVA was used to identify within and between group variations.

3.2.1.2 Socio-demographic Dimensions

Lifestyle clusters were identified using *socio-demographic* variables including age, income, household size, home type and disability. A similar approach to that outlined above was used to develop the clusters. Results were compared with those found by the previous method. Once the clusters were developed, ANOVA was used to analyse variations in travel behaviour, activity-engagement, and stated adaptation responses within and between the groups. This particular approach is, in some respects, the reverse of that being employed in section 1 above.

3.2.1.3 Travel Behaviour Dimensions

Travel behaviour variables were cluster-analyzed to develop groups with relatively homogeneous trip-making patterns. Information such as total daily trip tours, activities per trip tour, trip duration, number of people in auto, role in auto (driver versus passenger), and mode was used to define cluster dimensions. With the groups defined, ANOVA was then applied to distinguish differences in socio-demographic characteristics indicative of lifestyles, activity engagement, and stated adaptation responses to the road pricing survey.

By grouping the elderly population using the three different approaches outlined above, an optimal set of clusters could be chosen that best met the objective of establishing subgroups that had similar travel behaviour and responses to policy implementation. The basis chosen for the development of clusters relied heavily on the statistical measures which examined inter and intra-group variabilities. However, the final cluster structures were also dependent on a reasonable number of groups being identified, appropriate group sizes (small groups could not provide reliable estimates of probabilities for subsequent modules while large groups were too heterogeneous), ability to identify an individual with a cluster based on commonly available data, and the ability/ease to identify an individual with a group (see below).

Once the optimal groupings were identified, the key attributes which govern the clusters could be identified. Those attributes that did not show statistically significant differences between groups could be removed from the data matrix, and the cluster analyses rerun to develop the final solution. If the removed attribute was, in fact, not essential, cluster membership should remain unchanged. By removing the nonessential attributes that govern cluster membership, assignment (or *identification*) of new objects (which in the context of this study is a simulated elderly person) to a cluster is simplified. A new object could then be identified by computing a resemblance coefficient (e.g., Euclidean distance) which reflects its proximity to the established clusters. The object would be assigned to the cluster to which it is closest.

The simulation model was developed such that individuals with arrays of attributes from actual populations would enter the model's first module. The attributes coincided with those found critical to determine lifestyle group membership in the cluster analyses. Subsequent modules relied on this character set to assign activity patterns. The individual was then identified with one of the lifestyle groups using the method noted above.

3.2.2 Module 2: Development of Daily Engaged Activity Patterns

The second module of the simulation model assembled daily activity itineraries based on findings from activity information contained in the Portland METRO data set. As previously noted, there is a total of 16,843 individual activities listed for those over the age of 65 years. Information concerning type of activity, location, duration, distance, time of day, travel costs and mode(s) are recorded for each activity.

The specific activity types are listed as follows:

meals	household obligations	volunteer work
work	pick-up/drop off passengers	amusements (at-home)
work-related	visiting	amusements (out-of-home)
shopping (general)	formal entertaining	hobbies
shopping (major)	casual entertaining	exercise/athletics
personal services medical care	school	rest and relaxation
professional services	culture	spectator athletic events
household maintenance	religion/civil service	incidental trip
household or personal business	civic	tag along trip

The taxonomy used to categorize the activity classes depended largely on the frequencies of activity types among the elderly, as revealed by the data set. It was necessary to group the specific activities into broader classes to simplify the assignment process and reduce the number of cumulative distribution functions required. Most previous activity-based studies have proposed, or used, a broad taxonomy that divides activities according to whether they are *mandatory* or *discretionary* in nature. As noted in section 3.2.1, mandatory, or non-discretionary trips may be further classified as subsistence (work) or maintenance (purchase/consumption of goods/services to satisfy personal/household needs). Discretionary activities include leisure (entertainment, recreation, social visits) and those considered 'other'.

Module 1 associated each individual to a specific lifestyle group. Cumulative distribution functions were derived from the data set and a Monte Carlo technique used to assign stochastically the number of daily activities engaged in by an individual from a specific lifestyle group. For example, if an individual was identified with *Lifestyle Group A*, empirical distributions were then used to determine the probabilities of engaging in x total activities for a day. Empirical probability distributions, conditioned on the total daily activities, were then generated for each group based on survey results that describe the likelihood of engaging in different classes of activities for the day. For example, if an individual is assigned a daily total of only four activities then activities such as meals would be more likely than discretionary functions such as socializing or amusement. A flow diagram of Module 2 is presented in Figure 3.3.

Table 3.4 was developed to illustrate the method that was employed. The activity profiles of 14 survey respondents who were more than 90 years of age are listed. Although lifestyle groups were the basis for segregation, an age category is used simply for illustration. Using the data from the table, it is seen that the probability of an individual who belongs to this group engaging in 5 activities for a particular day equals 0.21 (= 3 of 14 respondents). Note that lifestyle groups segregated in Module 1 needed to be large enough to ensure reasonable levels of significance for the estimates of probabilities. Cluster sizes of at least 50 members were developed to provide statistical confidence in estimates. Furthermore, the aggregation of activities into categories resulted in a reduction of the number of matrix cells. Nevertheless, a common pitfall of Categorical Analyses is the lack of observations within some cells of the matrix. To compensate for a lack of observations within specific cells, Multiple Classification Analysis described by Ortuzar (1994) was employed to estimate some values.

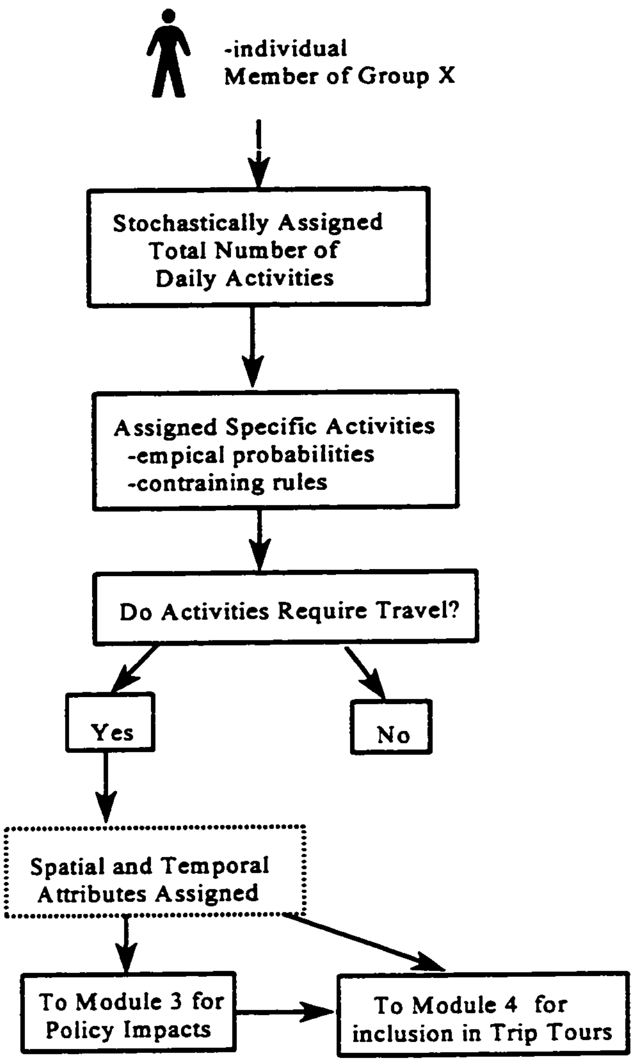

Figure 3.3: Module 2: Daily Engaged Activity Patterns

The next step was to use conditional probabilities to identify specific activities to be assigned to an individual. For example, if the individual was stochastically assigned a total of 5 activities for a day, data from the table can be used to develop probabilities to specify to which category each of these activities belongs. For example, if one undertakes 5 activities per day, the probabilities of each activity belonging to the category of meals, shopping, household maintenance, or amusement at home are listed:

meals	0.37	(12 of a total of 32 activities recorded for those who had daily averages of 5)
shopping	0.03	(1/32)
household maintenance	0.16	(5/32)
amusement at home	0.43	(14/32)
all other activities	0.00	(0/32)

These probabilities, in turn, were used to assign stochastically the five specific activities to the individual being simulated. A set of constraining rules were developed and employed to temper the maximum and minimum number of times specific activities could be assigned. For example, using stochastic assignment, there is a small probability of being assigned all 5 activities to a single activity class which in most cases would not be appropriate. The constraining rules were established on the basis of cumulative distribution functions of engagement for the different activity classes.

Table 3.4: Activity Engagement of Those Over 90 Years of Age

Activity (Code)	Survey Respondents														2-day Total
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	
meal (11)	5	5	7	6	6	6	6	2	4	5	4	6	7	5	74
shopping (14)				1		1		1							3
pers. services (16)							1				1				2
medical care (17)				2	2										4
house maint. (20)		2		2		1	2	3	2				2		15
house. obligat. (21)									2						2
pick/drop passngr.(22)									2						2
visiting (31)					1						4		3		8
religion (43)										1					1
amuse.@home (51)	4	4	1	3		1	5	4	2	7	4	5	1	6	47
amuse. out home (52)					5										5
hobbies (53)	4	6							1						11
exercise (55)	2			2	2		1			1	2	3	1		17
Total (2-day)	15	11	14	16	16	9	15	10	13	14	15	14	14	11	191
Average (1-day)	7	5	7	8	8	4	7	5	6	7	7	7	7	5	

Each activity listed in the matrix of Table 3.4 could be *tagged* with a requirement for travel outside the home. For some activities the distinction is obvious (e.g., visiting, amusement out of home, household maintenance, etc.); however, some activities can take place either within or outside the home (e.g., meals, medical care, etc.). This information is available within the data set since a variable indicating whether travel was required for each activity record is present. A distinction was made to identify whether each of the assigned activities required travel outside the home. This is an important attribute when trip tours were assembled in Module 4, or for the evaluation of policy impacts in Module 3.

For future, more advanced, versions of the model, a travel distance and time-of-day tag (attribute) could be assigned to each activity. These values could be generated according to empirical distributions of the specific activity and tempered by constraints (see Figure 1.5). These values would be useful in subsequent modules when trip tours were assembled and travel needs evaluated. Modifications to activity itineraries and trip tours precipitated by the testing of proposed policies, in Module 3, could also be linked to these attributes associated with each activity.

3.2.3 Module 3: Adaptation Model (Policy Induced Modifications)

An optional component of the activity-based model is a module that can effectively modify individual propensities to engage in specific activities based on stated response or adaptation to proposed policies. The module is optional in the sense that it can be employed when policy proposals are being evaluated. The module may be bypassed if the model is simply being used to assess trip-making levels/characteristics of a particular geographic area. The net effect of the module will be either a change in an individual's activity itinerary, or the profile of the trip tour that is assembled (or both). This study tested the module with the use of the results from the Portland stated adaptation surveys on road pricing as outlined in section 3.1.

Given that the respondents to the stated adaptation survey were drawn from the activity survey, the lifestyle group membership could easily be determined. An advantage of the categorical nature of the model is the capability to understand whether the proposed policies will have different effects on each subgroup. An underlying premise is that similar groups will react to policies in relatively consistent ways. The specific reaction to a policy dictates whether Module 2 or 4 will be affected. A requirement for the inclusion of any stated preference/adaptation survey results is the ability to identify the respondent with one of the predefined lifestyle groups.

To illustrate, possible responses to an increase in road pricing could yield the response that the respondent will *not make the trip at all.* As this specific survey response accumulates for part of the elderly within a specific category, the probability distributions in Module 2 would need to be modified to reflect activity engagement in the presence of these increased prices. As a result, the reduction in the number of trip tours as well as the underlying loss of activity participation can be understood for each elderly lifestyle group. Other responses such as *make trip less often*, or *engage in activity at home*, would have similar effects on travel needs. Responses such as *combine trip with others*, *look for a similar destination closer to home*, or *make trip at different time of day* will require adjustments to a future module that can more comprehensively combine activities into trip tours respective of scheduling constraints. Under the proposed framework, Module 4 combines activities into trips; however, given the restricted scope of this study, a simplified version of such a utility is described in the following section.

If the module is used to test a policy for which there are no stated adaptation information or empirical observations, detailed responses to the policy cannot be determined; however, the magnitude of the problem can at least be identified. Some conditional assumptions can be made to undertake a series of sensitivity analyses. For example, if a policy proposes that all drivers over the age of 85 years must be subjected to retesting, the impacts could be evaluated by applying a set of assumed consequences. If it were assumed that 20 percent would lose the privilege to drive, the characteristics of the trip tours of those involved can be analyzed to understand the activities that are affected as well as the alternative transportation resources/needs which would be required. Variables such as travel mode and role in auto (driver versus passenger) were linked with the trip tour since they are key to understanding the consequences of certain proposed policies. Mandatory versus discretionary activities can be highlighted to understand the transportation needs of those involved. Household structure (i.e., impact on a spouse or relative) would become a significant issue as modal substitution becomes a necessity for some trip tours. The proportion of drivers affected can then be altered to examine the sensitivity of its impacts.

3.2.4 Module 4: Development of the Number of Trip Tours

The scope of this project dictated that the aggregation of individual activities into tours needed to be addressed in a simplified manner. This was, at least partially, rationalized on the basis that 80 percent of all trip tours by the retired are simple one-stop circuits (as discussed in section 3.2.2).

In the fourth module, the number of trip tours was assembled as a simplified function of the total number of activities (by class) developed for an individual's daily itinerary. The number of tours was regressed against eight independent variables, representing the number of activities assigned to an individual from each activity class, to develop predictive relationships. This is a similar approach to that used by Goulias *et al* (1991) where a generalised least squares approach was used to predict the number of trip tours per household based on engagement in five classes of activities. A flow diagram of Module 4 is presented in Figure 3.4.

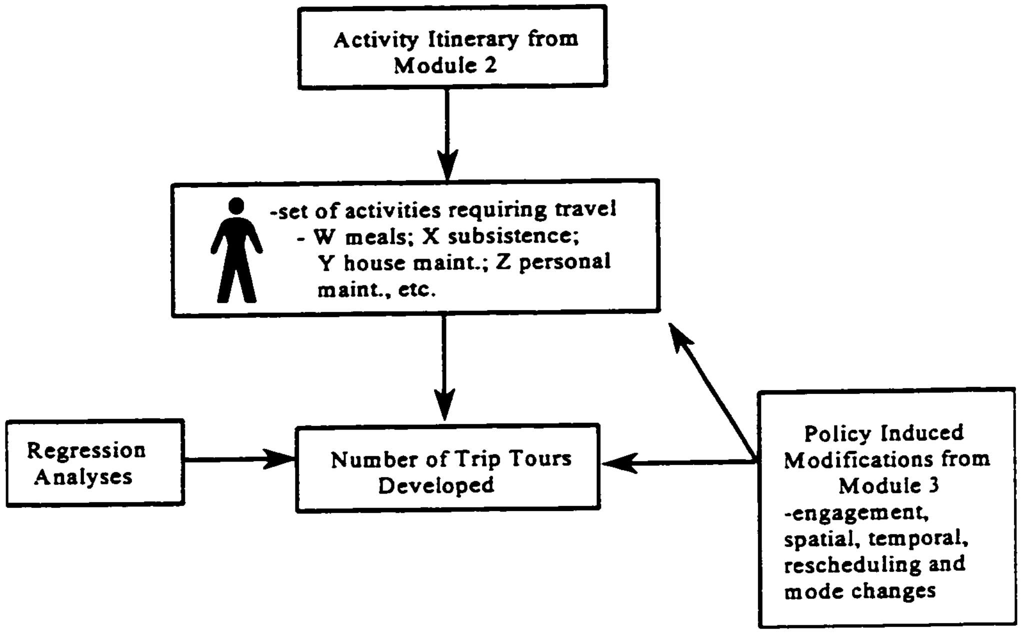

Figure 3.4: Module 4: Number of Trip Tours

Mode assignment was determined as a function of empirical distributions within lifestyle classes as well as activity type. For example, the data showed that a higher probability was associated with walking as the mode used to reach a recreational activity. Modes included personal vehicle (driver versus passenger), non-personal vehicle (e.g., taxi or friend's vehicle), light rail, bus, walk, or other.

3.3 Model Test Runs

Model runs were undertaken to validate the framework's ability to replicate base data and to test its sensitivity to the evaluation of proposed policy measures. The methodology used to accomplish these steps are described below.

3.3.1 Model Validation

A number of difficult issues arise when considering the validation of the base simulation model. Validation essentially refers to the model's ability to replicate correctly and accurately existing behaviour.

The initial step in model validation involved an examination of the conceptual aspects of the simulation process to ensure that it functions properly. The first *verification* process tracked individuals as they were processed through the model on a module-by-module basis. The simulation software, GPSS/H, has a "debugger" utility that facilitated this review. This step in the review essentially ensured that the model's *mechanics* were functioning properly.

The only economical means to ensure the model is accurately describing actual data was to compare observed activity itineraries or trips to those predicted by the simulation model. Informal and statistical comparisons of output variables were made to contrast predicted and empirical distributions. Given the data intensive nature of this process it was not possible to split the database in half to set aside data for validation. An external sample of data from the Vancouver, WA, survey (see Table 3.1) was used to validate the subject model.

3.3.2 Policy Issues

The model's ability to reflect accurately the effect of potential policy measures poses a paradox since one cannot "validate a forecast" unless it is a retrospective analysis. Kitamura (1997) noted that "validation may not be possible particularly for models designed to test policies (e.g., TDM measures) or changes in policies which have not been implemented." Pas (1997) suggests that perhaps the best approach is to ensure that the model can replicate base year data to undertake a sensitivity analysis to ensure that predicted policy effects are reasonable. This basic approach was used to determine whether the impacts associated with proposed policies targeting the elderly (e.g., license restrictions) appear reasonable. The road pricing stated adaptation survey contains empirical information that was incorporated in the model and the results aggregated. Ultimately, an implemented policy whose effects have been documented could be applied to this framework for validation.

CHAPTER 4

ELDERLY ACTIVITY ENGAGEMENT AND TRIP-MAKING

This chapter summarizes the results of a cross-sectional analysis of the data collected from the Oregon/Southwest Washington Household Activity and Travel Behaviour Survey (previously described in section 3.1). The data were analysed to provide a contrast of activity and travel patterns between the elderly and younger age groups. Daily engagement in different classes of activities is examined with a differentiation made between those requiring travel and those that do not. An underlying premise of the activity-based approach is that these patterns directly influence subsequent trip-making behaviour. Although the population is grouped only on the basis of age, ensuing chapters explore more sophisticated methods to segregate travellers into more homogeneous categories. The primary intent of this chapter is to illustrate that the elderly, as a whole, have markedly different activity patterns and subsequent travel behaviour apart from the general population. The analysis provides an examination of the patterns and structure of the variables that are used as the basis for categorization in Chapter 5. Furthermore, a benchmark is established against which the patterns of elderly subgroups can be compared.

4.1 Activity Engagement Patterns

The following sections document the general changes in activity patterns that correspond with advancing age, particularly beyond the age of retirement.

4.1.1 Daily Activity Engagement Rates

Survey respondents were asked to record all activities that lasted at least 30 minutes or involved travel outside the home. A summary of nearly 127,000 individual activities is presented in Figure 4.1. Daily participation rates are depicted for all activities as well as only those requiring travel. A marked reduction in travel for the participation in activities occurs beginning with the 75-79 age group. In contrast, the daily total number of activities undertaken seems stable, if not increasing slightly for those beyond the age of retirement. Despite this upward trend, a corresponding decrease in the participation of activities requiring travel poses some interesting questions concerning the travel needs and mobility patterns of the aged. The next step in the analysis was to gain a better understanding of the types of activities for which the elderly continue to travel.

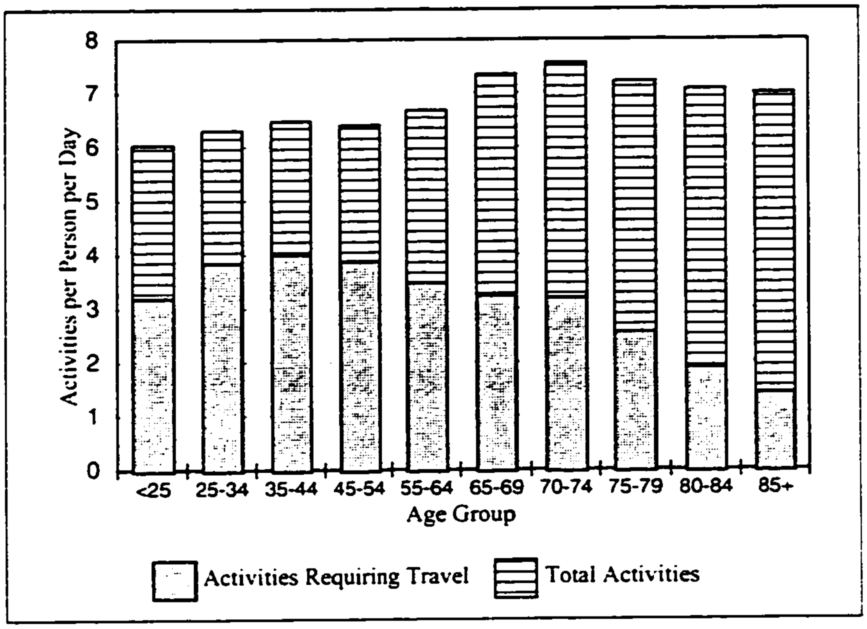

Figure 4.1: Daily Activity Engagement

Table 4.1 presents a summary of the daily frequency of activity engagement by age group as found using the Portland Metro survey. These data include both activities requiring travel and those engaged in at home. The summary information is based on nearly 127,000 recorded activities for almost 10,000 respondents. Note that the specific activities have been grouped into eight broader categories, namely: meals, subsistence, household maintenance, personal maintenance, social, amusement, recreation, and other. Furthermore, the categories are more broadly defined according to whether they can be considered mandatory or discretionary in nature. Although activities that are mandatory are normally a requirement for sustenance, there are instances when specific activities defined by these classes are more discretionary in nature. For example, travelling for a meal is, in fact, a highly discretionary activity. The patterns inherent in these data are illustrated in Figures 4.2 through 4.8.

Figure 4.2 presents the engagement of the different age groups in *mandatory* activities as a percentage of all activities in which they participate. The most profound change associated with advancing age is

Table 4.1: Average Daily Engagement Frequencies by Age Group

Activity Type		Age Groups										avg. for all ages	Sub-totals
		<25	25-34	35-44	45-54	55-64	65-69	70-74	75-79	80-84	85+		
MANDATORY:													
-meals	meals	1.43	1.44	1.45	1.46	1.66	1.90	2.01	1.98	2.02	2.24	1.52	1.52
-subsistence	work	0.15	0.83	0.87	0.91	0.61	0.20	0.08	0.08	0.06	0.02	0.55	
	work related	0.02	0.11	0.14	0.18	0.11	0.05	0.01	0.02	0.03	0.00	0.09	
	school	0.74	0.15	0.07	0.05	0.04	0.03	0.03	0.00	0.03	0.01	0.26	0.91
-house maint	shopping	0.29	0.42	0.46	0.46	0.48	0.61	0.59	0.46	0.30	0.35	0.42	
	shopping (major)	0.01	0.01	0.02	0.01	0.02	0.01	0.02	0.01	0.00	0.01	0.01	
	house/per. bus.	0.04	0.11	0.10	0.14	0.15	0.20	0.25	0.14	0.12	0.09	0.11	
	hshld. maintn.	0.18	0.45	0.54	0.51	0.70	0.89	0.88	0.83	0.80	0.73	0.47	
	hshld oblig.	0.03	0.19	0.17	0.08	0.06	0.09	0.10	0.06	0.09	0.05	0.10	1.10
-pers maint	pers. services	0.04	0.04	0.04	0.05	0.04	0.06	0.08	0.05	0.02	0.02	0.04	
	medical care	0.03	0.03	0.04	0.05	0.07	0.06	0.08	0.07	0.09	0.05	0.04	
	prof. services	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.09
DISCRETIONARY:													
-social	visiting	0.31	0.27	0.22	0.24	0.34	0.36	0.40	0.41	0.39	0.33	0.29	
	casual entrtnmnt	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.05	0.01	
	formal entrtnmnt	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	
	relg/civic services	0.06	0.03	0.05	0.06	0.07	0.09	0.10	0.10	0.07	0.07	0.06	0.37
-amusemnt	culture	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.03	0.01	0.00	0.01	
	amsemnt (hm)	1.54	1.04	1.03	1.05	1.26	1.56	1.69	1.77	1.99	1.87	1.28	
	amsemnt (out)	0.21	0.13	0.12	0.10	0.09	0.11	0.09	0.09	0.06	0.08	0.14	
	hobbies	0.06	0.06	0.09	0.10	0.18	0.25	0.25	0.26	0.24	0.26	0.10	
	spectator	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.00	0.02	0.01	0.02	1.56
-recreation	civic	0.02	0.01	0.03	0.03	0.03	0.05	0.05	0.05	0.03	0.03	0.03	
	volunteer work	0.01	0.01	0.01	0.02	0.02	0.03	0.03	0.02	0.02	0.01	0.01	
	exercise/athltcs.	0.15	0.13	0.13	0.12	0.10	0.14	0.15	0.13	0.07	0.05	0.13	
	rest /relaxation	0.26	0.27	0.28	0.30	0.32	0.33	0.39	0.42	0.49	0.59	0.29	0.46
-other	incidental trip	0.19	0.22	0.17	0.19	0.14	0.14	0.10	0.10	0.04	0.04	0.18	
	tag-along trip	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.02	
	pu. / drop pax.	0.15	0.30	0.38	0.22	0.13	0.11	0.13	0.08	0.04	0.03	0.22	0.42
Totals		6.04	6.31	6.48	6.40	6.68	7.34	7.55	7.21	7.07	6.99	6.43	6.43

the dramatic reduction in subsistence activities (work, work related, school). These activities account for more than 15 percent of all activities for those pre-retirement age, while the proportion drops to approximately 2 percent for those beyond the age of 70 years. *Meals* occupy a steadily increasing proportion of activity engagement for those beyond retirement. Interestingly, *household maintenance* takes on a more significant role for those between 65 and 75, while those in later years engage in this class of activity less and less.

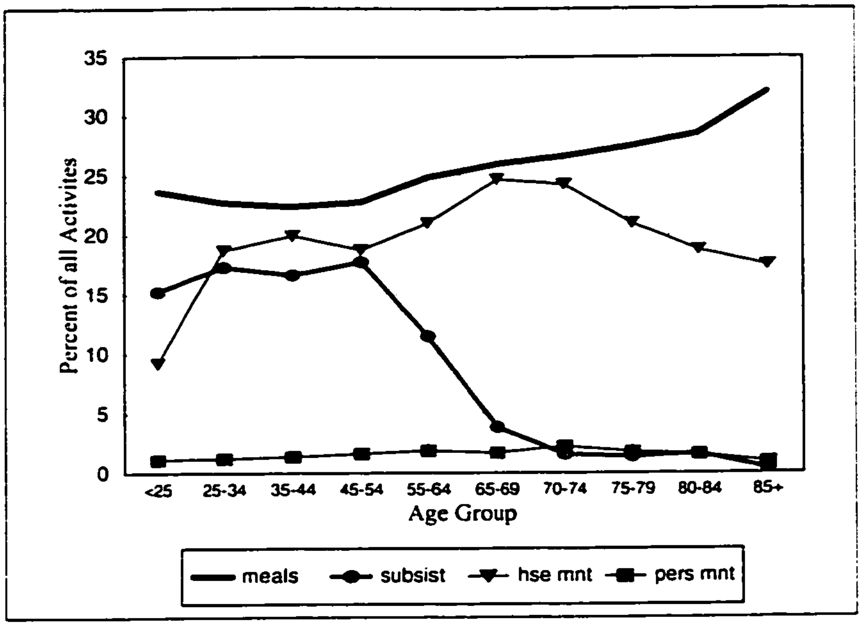

Figure 4.2: Mandatory Activity Engagement by Age

Figure 4.3 complements Figure 4.2 since it presents the same information for the *discretionary* activity classes (socializing, amusement, recreation, and other). The more significant trend associated with this plot is the increased percentage of amusement activities that accompanies advancing age. The decline in the percentage of *other* activities associated with aging stems from the inclusion of *passenger pick-up/drop-off* tasks within this group. This trend agrees with the findings of Jones *et al* (1983) previously presented in Figure 1.3.

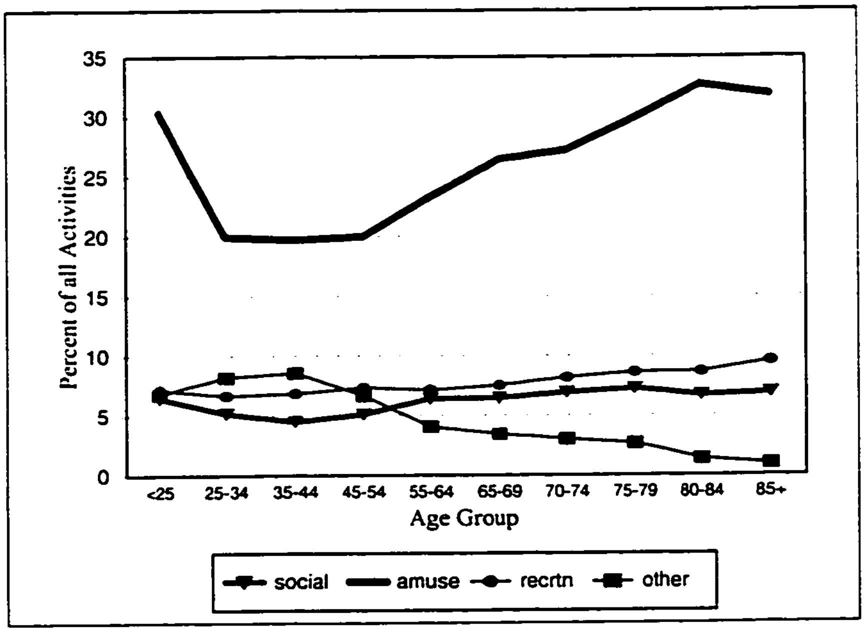

Figure 4.3: Discretionary Activity Engagement by Age

Figures 4.4 and 4.5 illustrate the demand for activities throughout the day. The probabilities of engaging in each of the eight activity classes are plotted for those under and more than 65 years of age. The y-axis of these plots reflect the probability of an individual participating in a particular class of activity for any given time period. For example, the probability that an individual who is less than 65 years old engaging in a meal is 30 percent between the hours of noon to 2:00 p.m. Stated differently, 30 percent of all those less than 65 years of age will have a meal during this time period. It must be stressed that more than one activity can, in fact, be undertaken during the same time period. Consequently, it is possible that the sum of probabilities for different activities can sum to values beyond 100 percent within common time periods. Note that the survey did not include home activities that required less than 30 minutes to complete so some activities may have been excluded for different individuals (e.g., quick meals, etc.).

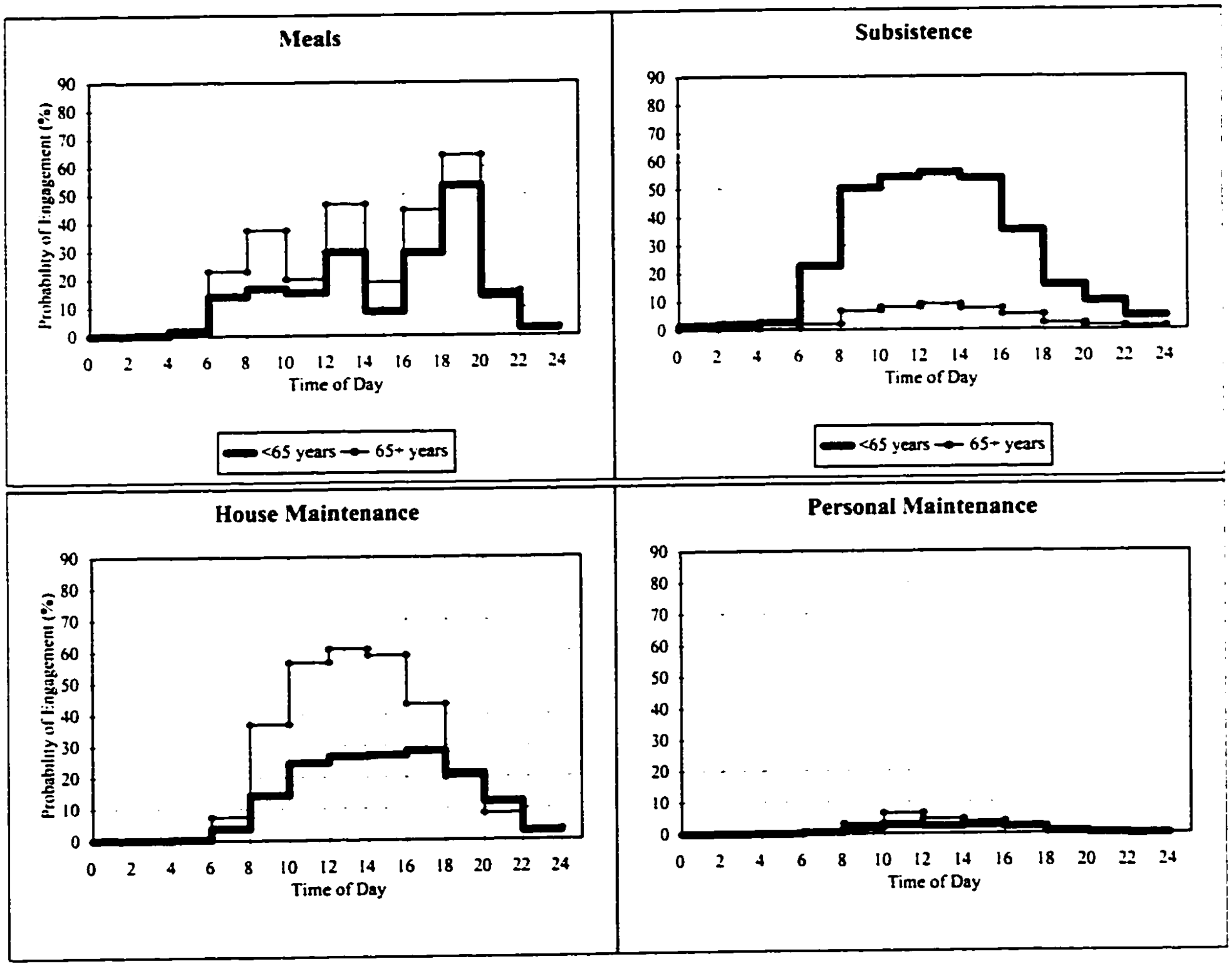

Figure 4.4: Probability Distributions of Mandatory Activity Engagement

Figures 4.4 and 4.5 present the mandatory and discretionary activities, respectively. Although the inclusion of only two large age groups provides a relatively coarse analysis, it does provide a basis for comparison with more homogeneous elderly groups identified in Chapter 5. Similar empirical probability distributions were used as inputs for the microsimulation model development (Chapter 6).

It is interesting to note the differences in activity engagement patterns of the elderly compared with those less than 65 years of age. Figure 4.4 illustrates that the older age group may be more regimented about having meals at traditional times. It is shown that the peak engagement of the elderly, as a whole, in activities such as household and personal maintenance, social, and recreation tend to occur during earlier times of the day compared with their counterparts (who are committed to work-related activities during these periods).

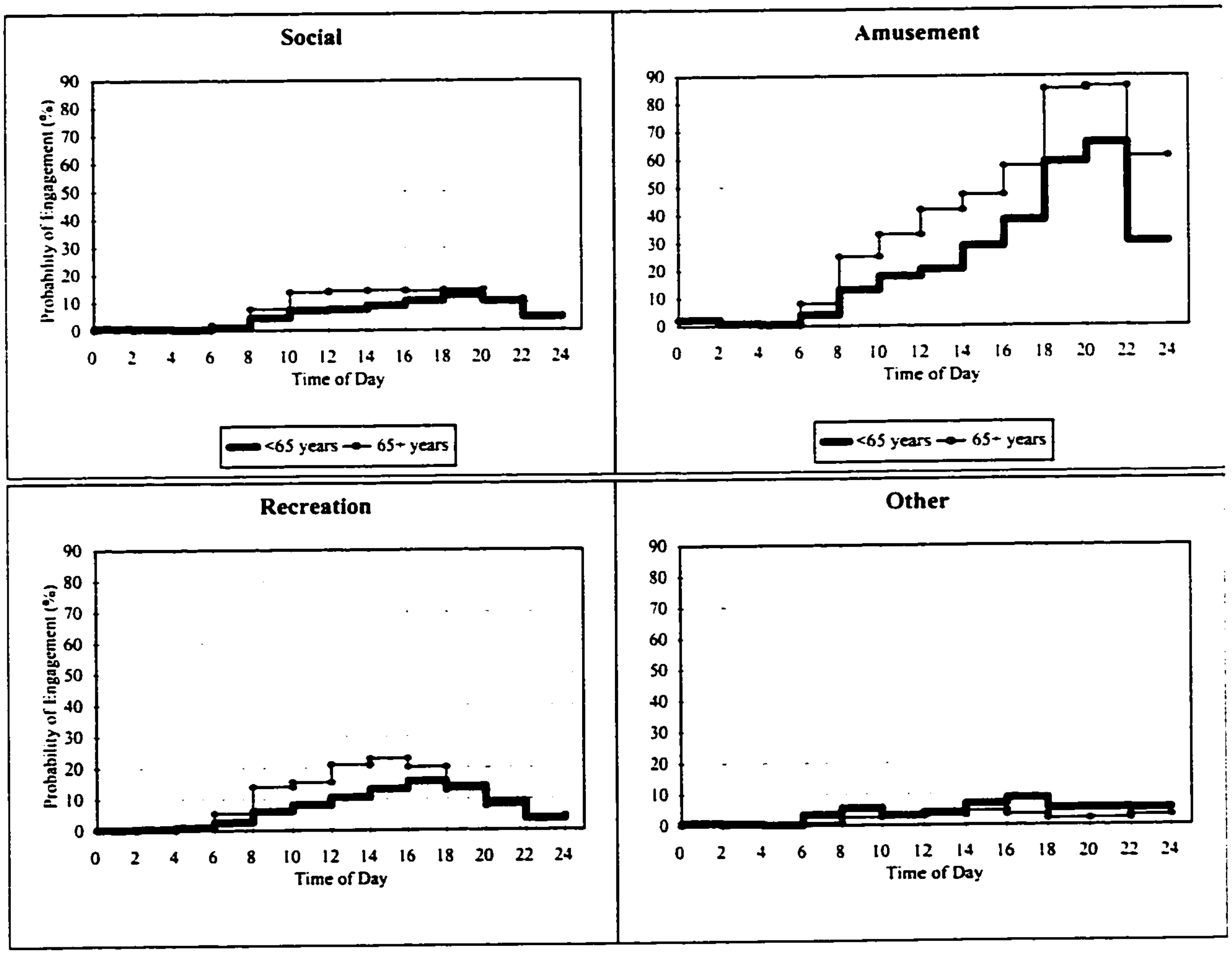

Figure 4.5: Probability Distributions of Discretionary Activity Engagement

4.1.2 Activity Engagement Requiring Travel

Since many activities can, in fact, take place within the home only those activities that the respondents travelled to were isolated and depicted in Figures 4.6 and 4.7. Some interesting differences evolve when these figures are compared with those previously presented. For example, meals accounted for a significant proportion of all activities (approximately 25 to 30 percent) undertaken by those over 65 years of age. However, as shown in Figure 4.6, meals only represent approximately 10 to 15 percent of all activities for which travel is required.

The activity class of *household maintenance* represents the most prominent reason for the elderly to travel. Beginning around age 65, nearly 40 percent of all activities requiring travel are for household maintenance. Note that for the very old (85 years and older) this class of activities represents nearly 50 percent of all activities reached through travel. The primary task contributing to this trend is *general shopping*.

One of the most dramatic differences that these plots highlight (compared with Figures 4.2 and 4.3) involves engagement in *social* activities. Although there is only a small rise in the engagement of social functions beyond the age of retirement (Figure 4.3), trip-making for social purposes becomes a dramatically more prominent reason for travel among the elderly (Figure 4.7).

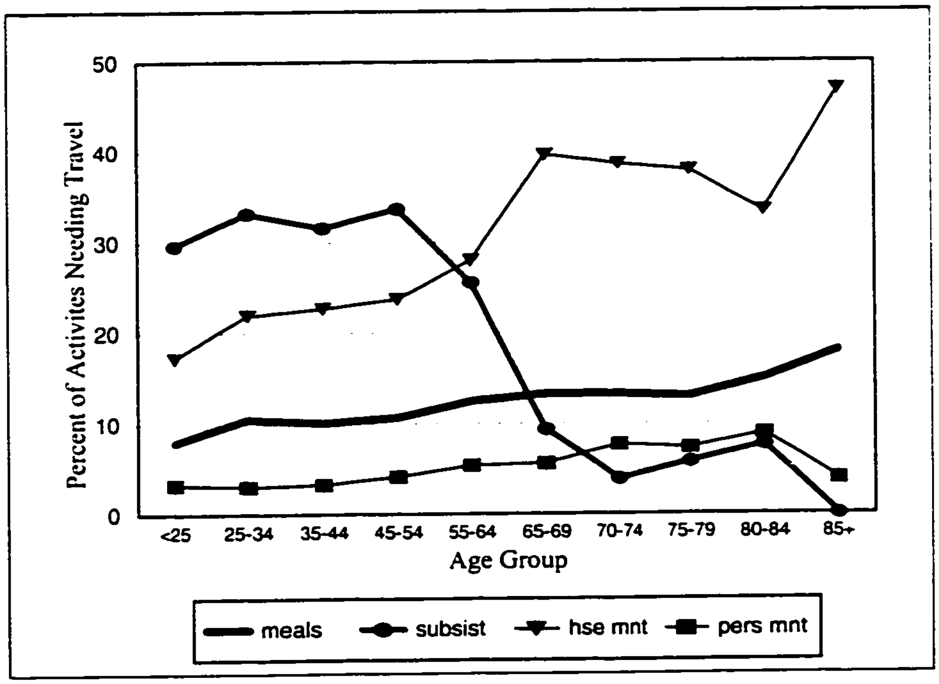

Figure 4.6: Mandatory Activity Engagement Requiring Travel

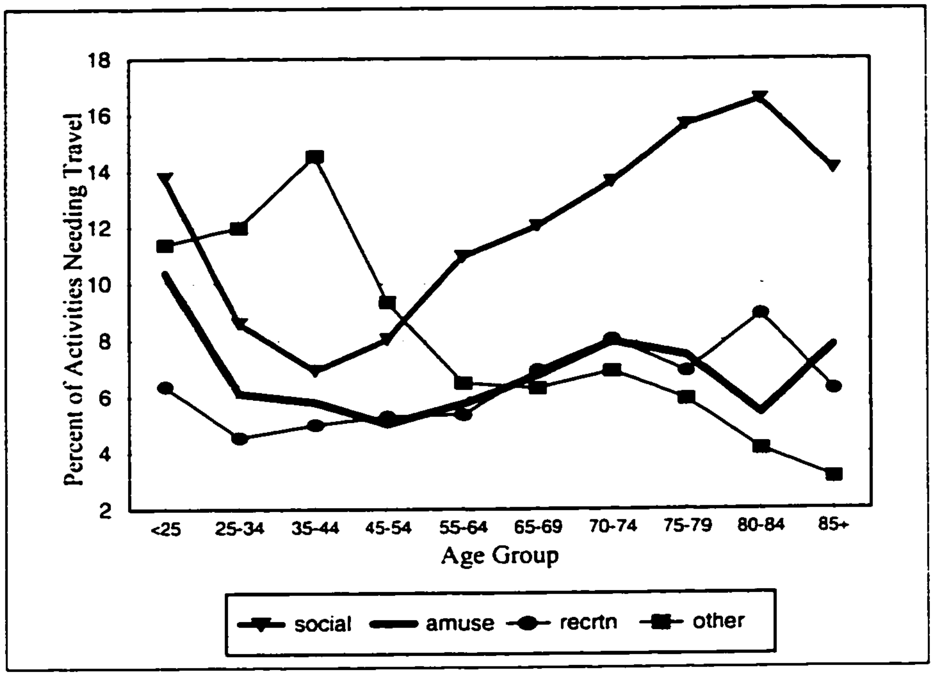

Figure 4.7: Discretionary Activity Engagement Requiring Travel

Figure 4.8 contrasts the percentage of mandatory versus discretionary activities that require travel. Intuitively, one might assume that as people age, travel becomes increasingly centred around mandatory activities. This plot, however, indicatives that the percentage of discretionary activities undertaken which require travel remains relatively constant with advancing age.

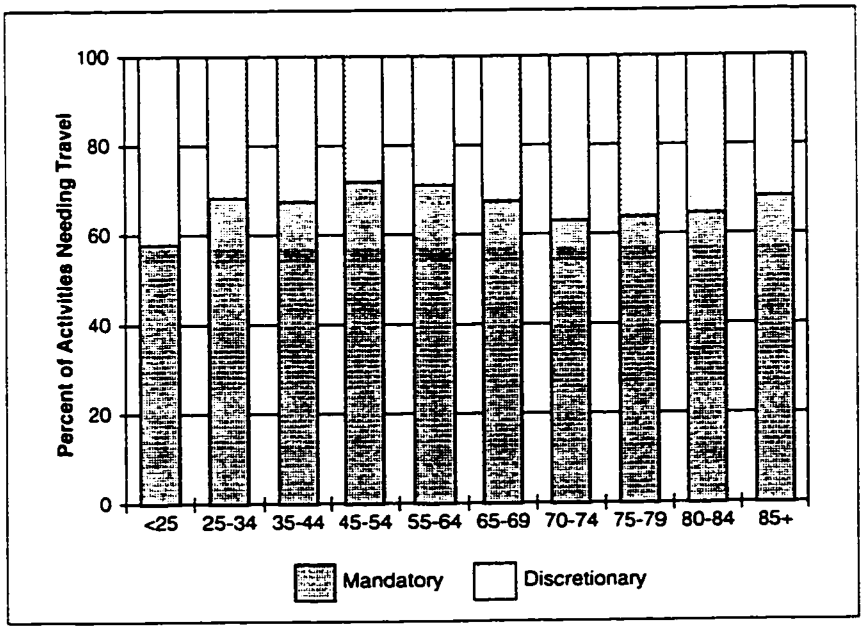

Figure 4.8: Mandatory/Discretionary Activities Requiring Travel

4.1.3 Activity Duration

In addition to understanding the differences in the types of activities engaged in by each of the age groups, identifying the average duration of engagement was also possible. This information helps to contrast the time-use behaviour of the elderly with other age groups, and can provide an input for activity scheduling in subsequent travel models. Figure 4.9 illustrates the average daily duration of engagement in each general class of activity for those under and more than 65 years of age. As shown, the older age group expends significantly less time in *subsistence* activities. This is an expected result given that most have retired beyond the age of 65 years. The elderly are shown to spend a greater amount of time in activities involving meals, house maintenance, and amusement. Much more detailed analyses involving activity engagement durations are presented in Chapter 5.

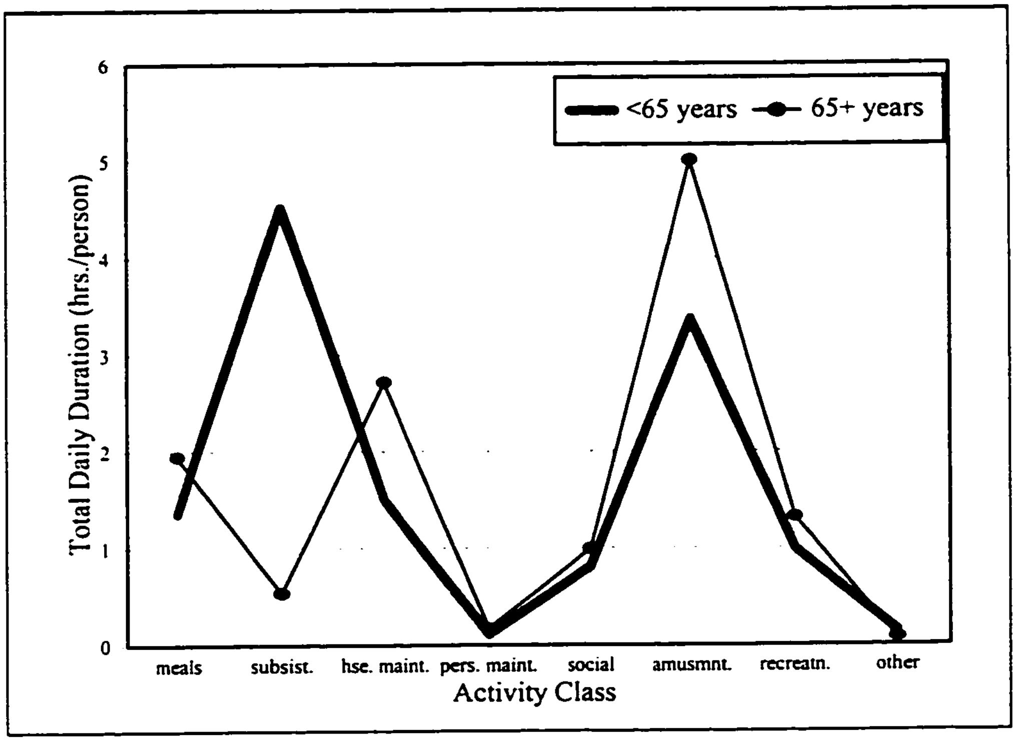

Figure 4.9: Daily Durations of Activity Engagement

Figure 4.10 presents the average duration of engagement for those activities where travel was required. For example, if someone under the age of 65 travelled to a meal, on average they would be expected to spend 1.9 hours participating in that particular activity. It is shown that for those 65 years of age and over the average duration of subsistence activities requiring travel is 5.0 hours while their younger counterparts averaged 6.8 hours. Recall from Figure 4.9 that, on average, the elderly spend relatively little time involved in subsistence activities. However, for those that do travel to work (or school), they spend less time in that activity. This is likely indicative of a disproportionate number of elderly who continue to work on a part-time basis. It is interesting that the older age group expends slightly more time in all other activities (except *other*) to which they travel.

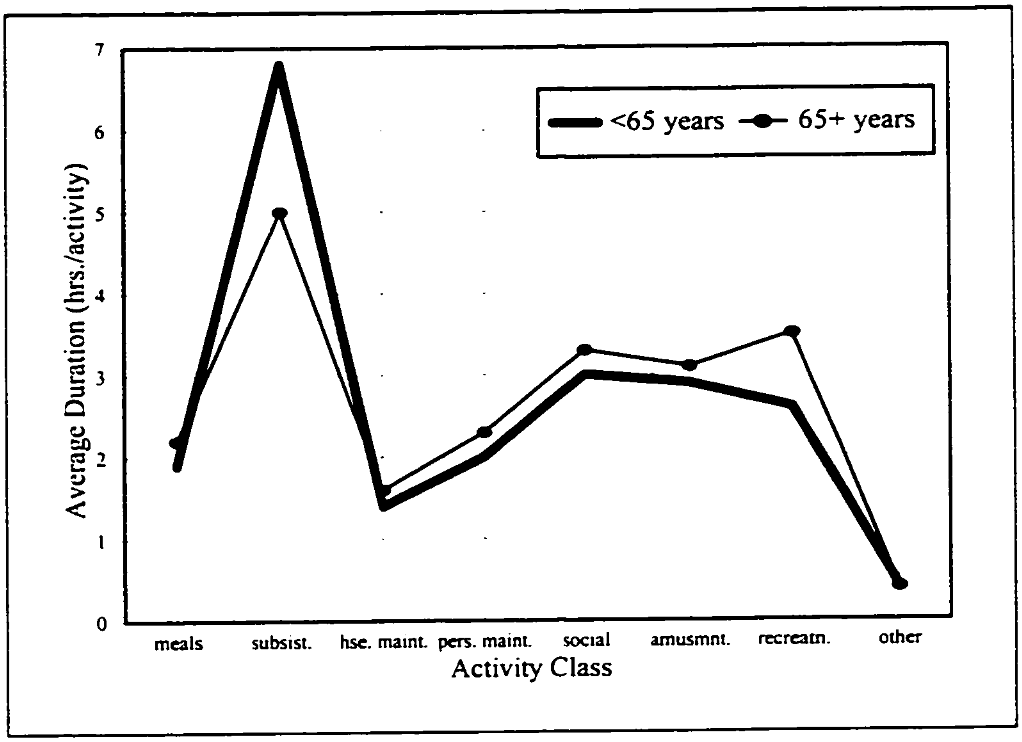

Figure 4.10: Average Duration of Activity Engagement When Travel is Required

4.2 Trip-Making Behaviour

Having achieved a clearer understanding of how activity engagement changes with advancing age, the next step involved contrasting the differences in travel behaviour. These differences, in turn, are used to illustrate the relationship between activity engagement and trip-making.

4.2.1 Daily Trip Tour Rates

The average number of daily trip tours undertaken by each age group is presented in Figure 4.11. Recall that a trip *tour* is defined as a collection and sequencing of different activities, which require travel, into a linked journey which starts and ends at home (refer to section 1.2). Therefore, a direct comparison between Figures 4.11 and 1.3 cannot be made. Figure 1.3 presents rates of conventional trips rather than rates of trip tours. To illustrate, if a person undertook the following activities: home - work - shop - work - home, the sequence would be counted as a single trip *tour* rather than three or four individual trips.

Although the general trend is similar to that of the average daily activities requiring travel (Figure 4.1) there is, interestingly, a significant increase in the number of trip tours for those aged 65 through 74. The peak in daily trip tours just beyond the age of retirement is followed by a steep decline for those over the age of 75 years.

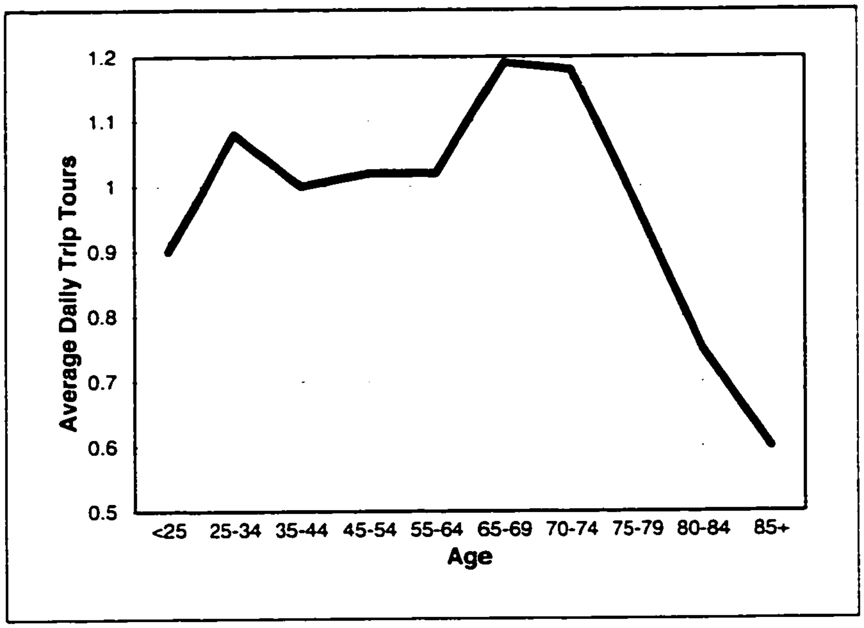

Figure 4.11: Daily Trip Tour Rate

4.2.2 Trip Tour Composition

An analysis of the survey data was performed to develop a distribution of the number of activities undertaken during a trip tour. Figure 4.12 presents a summary of this analysis for all age groups. The distribution for those under 65 years was informally found to be very similar with that for the combined group of those over 65.

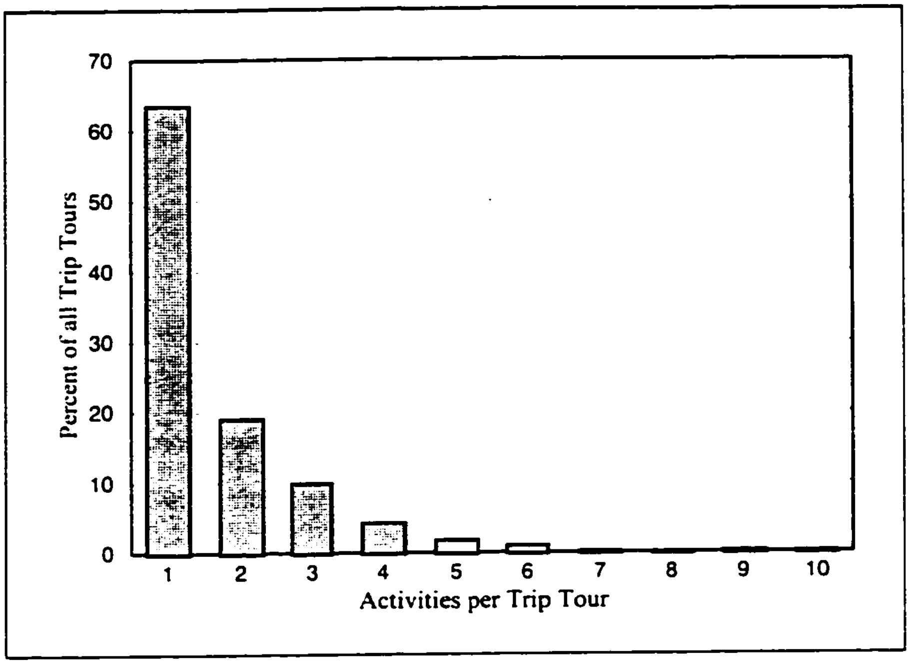

Figure 4.12: Activities per Trip Tour (all age groups)

A more disaggregate analysis of the number of activities per trip tour among the elderly is summarized in Table 4.2. It is interesting that the increasing proportion of trips tours which consist of only one or two activities as age advances beyond about 75 years.

Table 4.2 Proportion of Activities per Trip Tour for the Elderly

Activities per Trip Tour	Age Group				
	65-69	70-74	75-79	80-84	85+
1	0.63	0.61	0.64	0.69	0.77
2	0.19	0.20	0.22	0.19	0.14
3	0.09	0.11	0.09	0.07	0.05
4	0.06	0.04	0.04	0.05	0.01
5	0.02	0.03	0.01	0.01	0.01
6+	0.01	0.01	0.01	0.00	0.00

4.2.3 Mode Choice

Figure 4.13 summarizes the differences in mode choice between different age groups. The modes represented include the automobile, bus, bicycle, walking, and MAX (Portland's light rail system). These data closely match the findings of previous studies summarized in section 1.1.2. As illustrated, the auto is by far the preferred mode among all those surveyed. For most age groups, the auto is used for nearly 90 percent of activities requiring travel. The only significant difference is among the relatively young (under 35 years) and the very old (85 years and over). The data seem to suggest that among the very old, walking is the most common modal substitution for an auto trip.

The auto mode depicted in Figure 4.13 includes the use of both one's own personal car as well as a *non-personal* auto (i.e., taxi or a friend's vehicle). To distinguish between the application of these two uses of the auto, Figure 4.14 was prepared. As shown, there is a significant increase in the use of non-personal vehicles among those aged 75 and over. The underlying basis for this trend is that with advancing age many travellers switch roles from that of *drivers* to *passengers*. This trend is supported by the data presented in Figure 4.15. Note that the proportion of auto trips made as a passenger increases by a factor of up to four as one progresses from middle age to elderly.

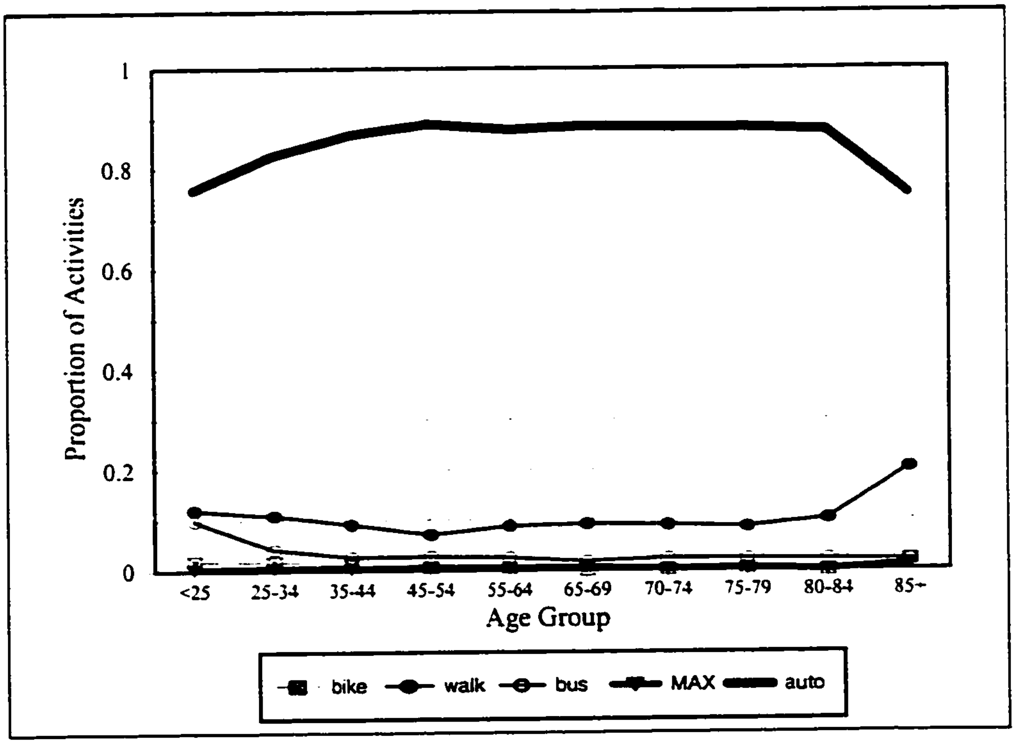

Figure 4.13: Mode Use

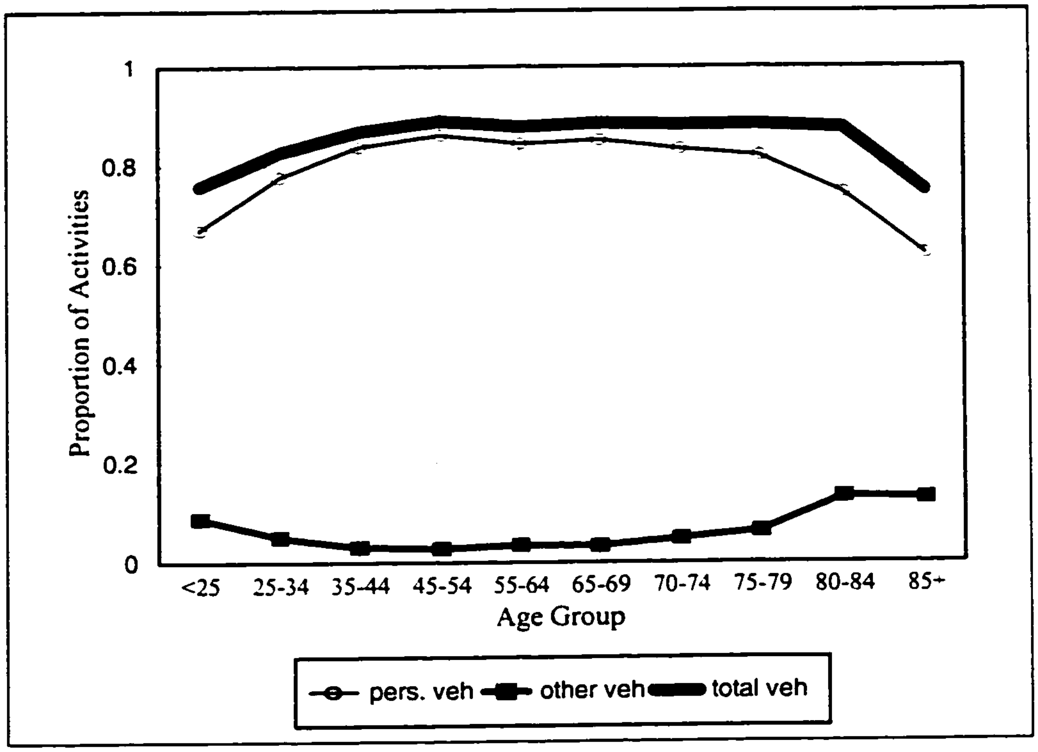

Figure 4.14: Automobile Use

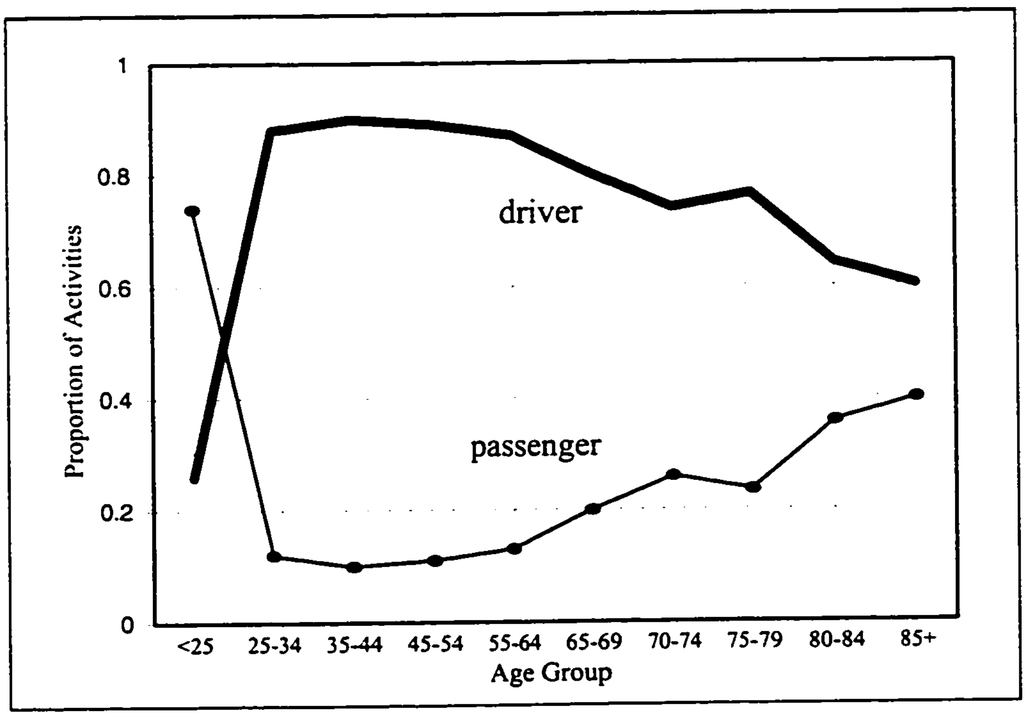

Figure 4.15: Trip-maker's Role in Personal Automobile

Directly related to the decreased use of the auto (as a driver) among older trip-makers is the sharp reduction in the percentage who hold a valid driver's license. The data depicted in Figure 4.16 show that among the survey respondents, there is a significant decline in the percentage of those who hold a driver's license, beginning at about age 70 among females, and age 80 for males. This trend, as previously discussed in section 1.1.2, is a result of two separate effects namely, the surrender of driving privileges by the elderly, and longitudinal demographic changes (e.g., many very old females never had a driver's license while this trend has abated among younger females). It is likely that the proportion of elderly females who have a driver's permit will increase during the coming years as today's middle-aged generations mature.

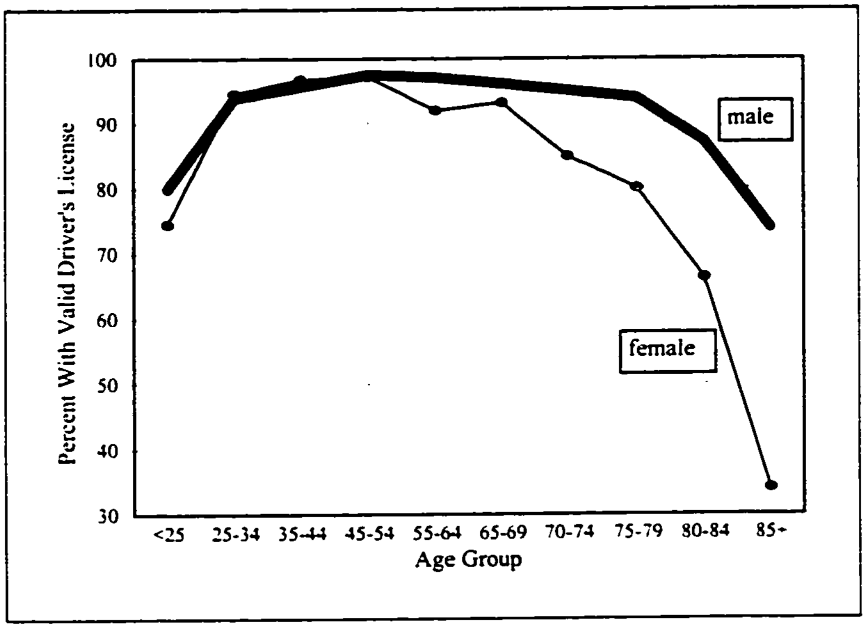

Figure 4.16: Driver's License Retention

Despite the increased frequency of the aged who travel by auto as a passenger, the average auto occupancy remains relatively stable from about age 45 and on (corresponding with the transformation to households without children). This trend is depicted in Figure 4.17. When the data was further examined by gender of the driver, it was found that the average auto occupancy of female drivers was slightly lower than that of male drivers for all age groups between 45 and 85 years. A higher rate was found for the younger groups and for those 85 years of age and over. These results for males agree with those found by the Institute of Transportation Engineers (1996) (see section 1.1.2). However, these results contradict ITE's findings that auto occupancy among female drivers steadily increases to an average of 2.6 for those more than 75 years of age.

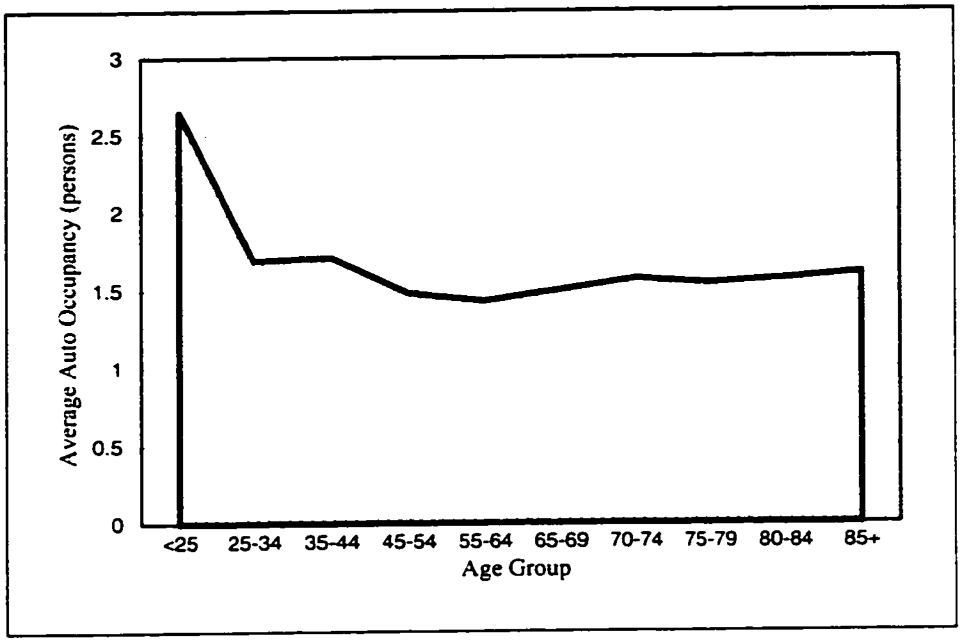

Figure 4.17: Average Auto Occupancy

4.2.4 Travel Duration

Extracting the distances individuals travelled to activities was not possible given the structure of the survey. However, the trip duration (i.e., travel time) was available for each activity as a proxy for distance. Figure 4.18 presents the average travel times for each of the activity classes. As shown, there are no discernible differences between the two age groups. Note that these data simply represent the trip duration when travelling to an individual activity and are not indicative of aggregate (e.g., daily) travel expenditures. No trends or patterns emerged when the ages were further disaggregated into smaller groups.

4.3 Summary

The results of the analyses undertaken in this chapter were used primarily for comparative purposes in subsequent chapters. While stratification of the elderly into age groups has revealed significant

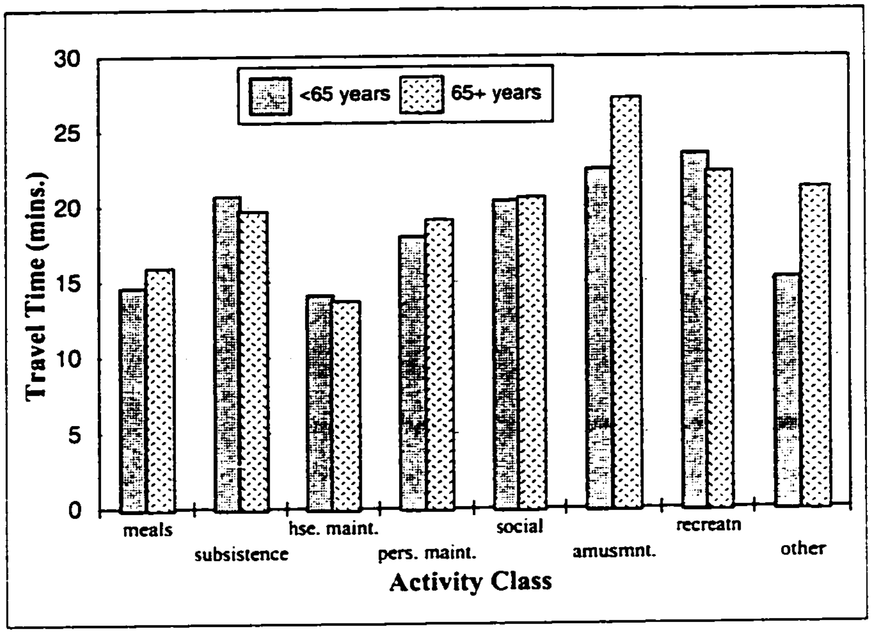

Figure 4.18: Travel Time Duration

differences in activity engagement patterns and resulting travel behaviour, the cluster analyses undertaken in the following chapter served to develop a more in-depth understanding of trip-making among the aged. Perhaps the most significant findings relate to the decreasing complexity of trip tours associated with advancing age. Although it could only be surmised at this point that this trend is related to decreased participation in *subsistence* and *other* activities, these linkages were quantified with the linear regression models developed in Chapter 6.

The analyses summarized in this chapter have revealed the following major differences in activity participation and travel between the elderly and younger age groups:

(1) The daily total number of activities undertaken per person averages between 6 and 6.5 for all age groups under 65 years. This average increases to between 7 and 7.5 for the elderly age groups.

(2) Beginning at about the age of 75, there is a marked reduction in the daily number of activities requiring travel.

(3) Following the age of retirement, subsistence activities only represent about 2 percent of all daily activities, down from an average of approximately 17 percent for those who are middle-aged.

Meals and amusement activities account for increasing proportions of the daily itineraries among the elderly.

(4) Beyond the age of 25 years, the ratio of discrete/mandatory activities remains relatively constant.

(5) The activity class of household maintenance is the most prominent reason for travel (accounting for nearly 40 percent of all activities away from home) among the elderly age groups. This compares with only about 25 percent for the younger age groups. Social activities represent an increasingly larger proportion of the activities requiring travel beyond the age of retirement.

(6) The elderly spend significantly greater amounts of time engaged in activities such as meals, house maintenance, and amusement than their younger counterparts. As expected, they were shown to spend less time participating in subsistence activities.

(7) The average number of daily trip tours for middle-aged individuals is around 1.0. This rate increases to approximately 1.2 for those aged 65 to 75, then steadily drops to about 0.6 for those over 85 years.

(8) The number of activities per trip tour is relatively constant until about age 65 when the percent of tours with only one activity steadily increases with advancing age. Similarly, the number of multi-stop tours decreases among older age groups.

(9) Mode choice was shown not to vary significantly with age except for those over 85 years. Interestingly, the very old showed an increased propensity to walk to activities away from home with a corresponding decrease in auto use.

(10) The percentage of activities accessed by the elderly travelling in automobiles as passengers constantly increases from about 15 percent at age 65 to approximately 40 percent at age 85.

(11) There is a steep decline in the proportion of those who retain their driver's license that corresponds with advancing age. The decline is more dramatic among females which may be due, in part, to cohort effects.

(12) There appears to be no change in the travel duration (a proxy for trip distance) with advancing age.

CHAPTER 5

DELINEATION OF ELDERLY LIFESTYLE GROUPS

The efforts undertaken to delineate sub-populations of the elderly that have distinctive lifestyle attributes are presented in this chapter. A fundamental premise underlying this effort was that members of common lifestyle groups would have distinct patterns of activity engagement and therefore characteristic travel behaviour. Partitioning the elderly would therefore allow the development of an activity-based travel model that processes individuals by applying utilities and algorithms unique to specific clusters.

Since the dimensions which define lifestyle are somewhat ambiguous, the basis for stratification was not definitive. However, it must be stressed that any preferred classification basis is highly dependent on the final use of the cluster information. For this study, a primary use of the model framework was to provide a means of evaluating the impacts of proposed policies targeted for the elderly. Segregation of the elderly into subgroups must recognize the typical bases for policy implementation. In other words, most policies that would affect the travel behaviour of the elderly (see section 1.1.3) tend to be delineated along socio-demographic and economic dimensions. For example, proposed mandatory retesting programs for elderly drivers typically discriminate based on age. Many proposed policy changes to public transportation have economic or physical disability overtones associated with them.

Also related to the issue of final use of the clusters is the fact that the simulation model was to be designed so that individuals could be identified with a specific cluster based on commonly available observational data (i.e., typical socio-demographic and census data). These prerequisites all but excluded clusters formed on the basis of dimensions other than socio-demographic from inclusion in the model structure. However, the possibility had to be explored that clusters formed using activity engagement variables, for example, could have highly distinctive partitions in socio-demographic characteristics. This would allow individuals external of the data set used to develop the clusters to be identified to the appropriate cluster based on commonly available socio-demographic variables. Given this possibility, a three-pronged approach was employed to develop the clusters separately on the basis of:

(1) Activity engagement.
(2) Socio-demographic variables.
(3) Travel behaviour.

Application of the three distinct perspectives to develop clusters also provided insight into the relationships that exist between these dimensions thereby enhancing the understanding of elderly activity and travel behaviour.

Although attempts were made to identify clusters using combinations of the above approaches (e.g.. using both socio-demographic and travel behaviour variables) none of the results are presented. It was found that any resulting subgroups provided weak delineations across most dimensions. Furthermore, there was often only one large subgroup identified besides several very small subgroups. Overall, the clustering on too many varied dimensions weakened the ability to delineate subgroups with homogeneous and distinct characteristics.

Using activity engagement as the basis for cluster development reflects the notion that one's behavioural pattern is the result of lifestyle characteristics. An approach using socio-demographic variables to define lifestyle is consistent with previous work outlined in section 2.5.1. Finally, clustering on the basis of travel behaviour provided a means to work backwards from a solution of groups with homogeneous trip-making characteristics to learn if they have common socio-demographic or activity engagement patterns.

It should be noted at the onset that the nature of the Portland Metro survey has excluded some sectors of the elderly population that would likely represent distinct lifestyle groups with special travel needs. The survey was geographically stratified with respondents selected at random within each zone. Initial contact was made by telephone, with subsequent communication being either through the mail or with further telephone calls. The aged who are either illiterate, visually or hearing impaired may have been unable to participate. Furthermore, the elderly who were either hospitalized or institutionalized were likely missed given the survey design.

The following sections describe cluster development, interpretive descriptions of the clusters, and analysis of variance techniques used to identify statistical variations between the groups. A further premise tested in this chapter is that individuals with similar characteristics will have relatively homogeneous reactions to proposed policies.

5.1 Cluster Analysis Based on Activity Engagement

Several recent explorations of the linkage between one's lifestyle and the corresponding travel behaviour were presented in section 2.5.1. Although different definitions of *lifestyle* exist, most would agree that time-use (or engagement in activities) is a measurable attribute that varies between distinct lifestyle groups. This section of the study developed clusters or groups of the elderly survey respondents strictly based on time-use patterns. Variations in socio-demographics, travel behaviour and stated adaptation responses for each of the resulting clusters were then analyzed to identify any significant differences between the groups.

The number of hours of engagement in each of the eight activity classes (previously defined in section 4.1) provided the foundation to segregate the 1,150 elderly respondents. These quantities were extracted from the activity-based survey data, resulting in two-day totals being used for the analyses. The following sections describe the results of the analyses.

5.1.1 Preliminary Cluster Analyses

An extensive series of cluster analyses was undertaken so that the best grouping could be developed based on activity engagement. As previously noted, a hierarchical method was used to develop initial cluster centres necessary to employ the K-means approach which, itself, is an iterative partitioning technique. Recall that the use of the K-means technique was necessary given the large number of respondents in the dataset.

The agglomeration schedule maps the formation of clusters through the hierarchical process. Principio and Pas (1997) caution that

> "...the information lost increases very slowly initially as a large number of small clusters are formed, then it increases at a more modest rate, and finally, when there are few clusters, a great deal of information is lost when two clusters are combined."

To illustrate how this criterion was monitored in the current study, the following example is cited. As the number of clusters was incrementally decreased, a cluster containing respondents who had accumulated a large number of work hours would eventually merge with another group who did not have similar work patterns. This merger would, in effect, eliminate or mask a sub-population of the elderly who remain in the workforce beyond the typical age of retirement. When distinct clusters like this are combined, subsequent cluster solutions were considered too coarse for further consideration.

The selection of final cluster solutions was based on the following objective and subjective criteria:

(1) Limits to the size of clusters were set at a minimum of 50 individuals (to provide significance for subsequent statistical analyses) and a maximum of approximately 500 individuals (to provide cluster sizes of the same order of magnitude and to ensure meaningful segregation of the 1,150 respondents).

(2) The agglomeration schedules of clusters were carefully examined to ensure well structured, and well-separated cluster centres.

(3) The clusters had to be identifiable and interpretable.

(4) Cluster structure had to agree with expected or intuitive results (e.g., one would *expect* a cluster of disabled or highly immobile elderly respondents).

Preliminary analyses were undertaken to determine a range of cluster sizes most likely to yield an optimal solution. In this context, optimal refers to a solution which maximizes the information described by reasonably few clusters. Once the range was established, more detailed investigations were conducted to produce the final solution. The SPSS statistical software package has an *initial cluster centre* algorithm that undertakes an initial pass through the dataset and selects k (corresponding to the number of clusters being developed) cases that are well separated to be used as the initial centres for the iterative process. This utility was employed to develop preliminary solutions with 2 to 15 clusters that were evaluated for further consideration.

As noted above, the information (or variance) explained by the clusters will decrease as the number of clusters is reduced. For this study, segregating the data into as many as 1,150 clusters was possible (i.e., one for each observation). The proportion of information accounted for by the clusters can be defined as (Pas, 1982):

$$I_G = 1 - (WSS_G / TSS) \qquad [5.1]$$

where,

$$WSS_G = \sum_{g=1}^{G} \sum_{i=1}^{N_g} \sum_{l=1}^{L} (X_{ilg} - \overline{X}_{lg})^2 \qquad [5.2]$$

$$TSS = \sum_{g=1}^{G} \sum_{i=1}^{N_g} \sum_{l=1}^{L} (X_{ilg} - \overline{X}_l)^2 \qquad [5.3]$$

I_G	=	information explained by G clusters,
WSS_G	=	within-group sum of squares for G groups,
TSS	=	total sum of squares,
X_{ilg}	=	location on dimension l of observation i in group g,
$\overline{X}_{lg}$	=	mean location on dimension l of observations in group g,
X_l	=	mean location on dimension l of all observations,
N_g	=	number of observations in group g, and
L	=	number of dimensions in the real-space configuration.

In this context, I_G is equal to a coefficient of determination (R^2). Since R^2 is a more recognized term among transportation planners, I_G will be henceforth referred to as R^2. Note that the value of R^2 is 0 when the data are aggregated as a single group. The value of R^2 will increase to a value of 1 when the number of clusters equals the number of observations. Figure 5.1 depicts the relationship of R^2 with the number of clusters used to segregate the data. It is shown that beyond about seven or eight clusters, the incremental increase in R^2 with the addition of each cluster becomes minimal. This concept is more clearly illustrated in Figure 5.2 where the incremental information explained with increasing numbers of clusters is depicted. Referring to the figure, it is seen that the value of 10 percent corresponds with a five cluster solution. This means that by increasing the number of clusters from 4 to 5, an additional 10 percent of the variance (or information) is explained. These data agree with Pas' statement that the incremental contribution of additional clusters becomes less and less significant.

The information in these plots was used to help establish the range of clusters to be considered for more detailed analyses. For example, fewer clusters than four or five would result in significant loss of information, while more than seven or eight adds little to the explanation of the variance. Furthermore, these preliminary analyses showed that solutions with six or more clusters would have at least one

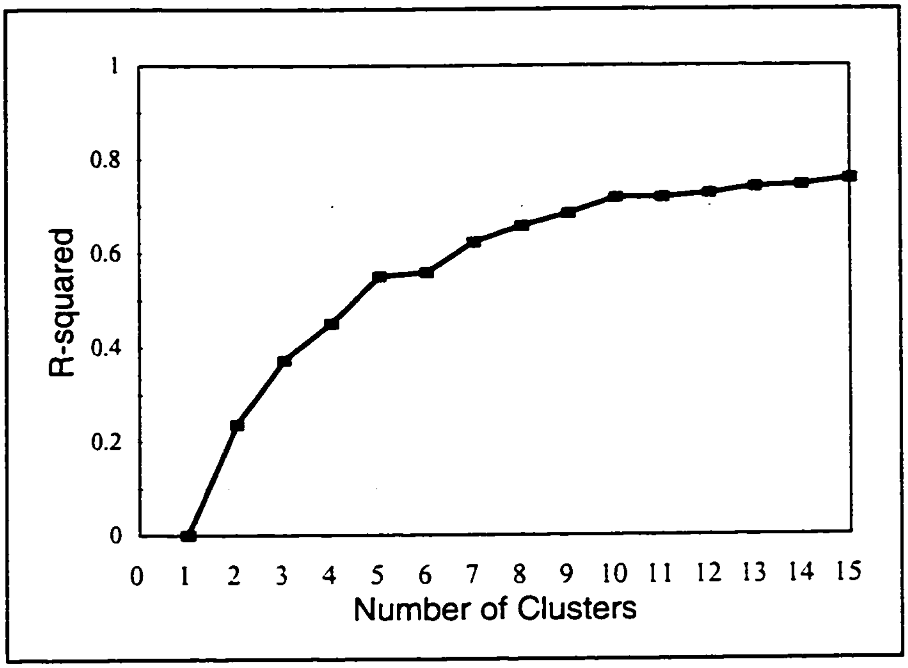

Figure 5.1: R^2 Relationship With Number of Clusters (Activity Engagement Clusters)

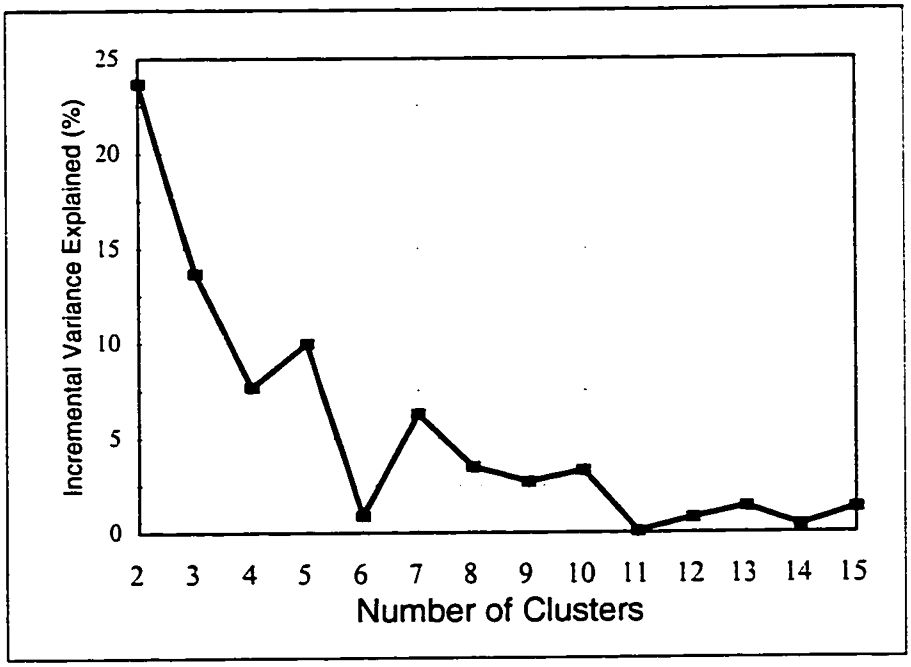

Figure 5.2: Incremental Information Explained With Increasing Number of Clusters (Activity Engagement Clusters)

cluster with fewer than 50 observations, while solutions with less than four clusters would have one group with more than 500 members. Based on these findings, a range of four to seven clusters was selected for more detailed investigation to produce a final solution.

The first step in developing a final solution was to more formally establish the initial cluster centres (a point in Euclidean space defined by the dimension of each of the eight activity classes) used as a starting point of the K-means technique. To construct the initial cluster centres, a random sample of 250 cases was selected from the data set to be subjected to both a UPMGA and Ward's Algorithm hierarchical cluster analysis. Recall that these algorithms cannot effectively manipulate data sets larger than approximately 400 observations due to computing constraints. Furthermore, the *initial cluster centre* algorithm imbedded in the SPSS software was applied to the data set as a third method to develop cluster centres. All three approaches were used to develop initial centres for four to seven cluster solutions.

Applying each of the initial cluster centres to the K-means technique for the full data set, a final five-cluster solution was selected for detailed examination based on the previously noted criteria. The final solution was developed from a set of initial centres generated by Ward's Algorithm. Interestingly, the alternative five-cluster solutions derived from either UPGMA or with SPSS's *initial cluster centre* program were similar. The four, six, and seven cluster solutions were rejected primarily because of the presence of extremely small or large cluster sizes.

5.1. 2 Description of Activity Engagement Clusters

Table 5.1 presents the final group sizes developed through the five-cluster solution. As shown, the groups range in size from 73 to 423 people. Each cluster is given a label that was subjectively assigned based on the group's dominant activity engagement characteristics. For example, cluster number 3 is called the *Relaxers*. This label is assigned based on the observation that this group engages in, on average, more than 15 hours of activities from the 'recreation' class (during a two-day period). Furthermore, as previously noted in Table 4.1, the primary specific activity within the recreation class is 'rest and relaxation'. Table 5.2 details the cluster means of participation in each activity class for the five clusters that have been identified.

Table 5.1: Distribution of Survey Respondents Across Activity Engagement Clusters

#	Cluster Label	Cluster Size	Percent of Sample
1	TV Viewers	345	30.0
2	Workers	85	7.4
3	Relaxers	73	6.3
4	Shoppers	224	19.5
5	Active Socializers	423	36.8
	Entire Sample	1150	100.0

Table 5.2: Activity Engagement Cluster Means

	Activity Engagement Cluster (mean participation over 2-day period; hours)						
Activity Type	TV Viewers	Workers	Relaxers	Shoppers	Active Socializers	Entire Sample	F Statistic
Meals	3.5	3.1	*2.8*	3.9	**4.5**	3.9	17.5*
Work/school	*0.1*	**11.8**	0.2	0.2	0.3	1.1	1210.8*
House Maintenance	3.4	2.4	*2.3*	**12.8**	4.4	5.4	452.0*
Personal Maintenance	0.2	*0.1*	0.3	0.2	**0.5**	0.3	3.7*
Social	*0.8*	1.2	0.9	1.3	**3.6**	2.0	44.5*
Amusement	**16.9**	6.3	*3.9*	6.3	8.2	10.0	544.7*
Recreation	1.4	1.5	**15.2**	*1.3*	2.4	2.6	415.8*
Other	*0.1*	**0.3**	0.2	0.1	0.2	0.2	1.8

* Statistically significant at the 0.05 significance level.

Note: **Bold** typeface indicates the **highest** mean for a particular activity type.
Italics typeface indicates the *lowest* mean for a particular activity type.

The first activity engagement cluster identified is referred to as *TV Viewers*. This group represents 345 people, or 30.0 percent of the sample. As shown in Table 5.2, they engage in an average of 16.9 hours of ***amusement*** type activities, the vast majority of which tend to be 'in-home amusement' activities. This participation level is well above that observed in any other cluster. Furthermore, this group works, socializes, and engages in *other* activities the least of any of the five clusters. Their participation in the remaining activity classes including meals, house maintenance, personal maintenance and recreation are all less than sample means.

The *Workers* lifestyle group contains only 85, or 7.4 percent of the sample. This group is distinguished based on their high participation in the subsistence (work/school) activity class. Their engagement of 11.8 hours, or nearly 6 hours per day, indicates that these cluster members still actively participate in the workforce. The only other distinguishing characteristic is that they participate in personal maintenance activities the least among the five clusters.

As noted earlier, the *Relaxers* are characterized by their propensity to participate in the recreation class of activities (which is dominated specifically by 'rest and relaxation' activities). This group is the smallest of the five clusters with only 73 members, or 6.3 percent of survey respondents. A full 15.2 hours, on average, is expended by group members on recreational activities. The next closest group only spends 2.4 hours on this activity class. Further characteristics of this group are that they spend the least amount of time engaged with meals, house maintenance, and amusement.

Shoppers are delineated because of the disproportionate amount of time engaged in the house maintenance class of activities. The label *Shoppers* is used because the specific activity of 'general shopping' dominates the house maintenance activity group (Table 4.1). There are 224 members assigned to this cluster, or 19.5 percent of the entire sample. The only other notable characteristic of this group is that they engage in recreational activities the least of any of the other clusters.

The final activity engagement cluster has been termed *Active Socializers*. It is the biggest group including 423 survey respondents, or nearly 37 percent of the sample. Group members average the largest amount of time engaged in the social, meals, and personal maintenance classes of activities. Furthermore, they have the second highest average participation in the house maintenance, amusement, and recreation activity classes.

Table 5.2 also presents values of the F statistic determined from analysis of variance undertaken to examine the strength of the overall differences in engagement times spent in the different activity classes across the five clusters. The F values were compared with tabulated values to test for the statistical significance of differences between the five lifestyle clusters. As shown, the engagement levels in seven out of eight of the activity classes were found statistically different across the groups at the 5 percent significance level. Observed significance levels would, in fact, show that all of the groups are different at the 1 percent significance level. There were no statistically significant differences between the clusters in the amount of time engaged in the *other* activity class.

Such strong results of the F statistic should not necessarily be construed as a complete validation of the cluster formations. Aldenderfer and Blashfield (1984) caution that

> ".....cluster analysis methods, by definition, will separate entities into clusters that have virtually no overlap along the variables being used to create the clusters. Significance tests for differences among the clusters along these variables should always be positive."

The cophenetic correlation coefficient is commonly used as a means to validate a cluster solution. The coefficient essentially measures how much the clustering method distorts the information used as input before the output is produced. However, it can only be applied when a hierarchical agglomerative method of clustering is used to generate final cluster centres.

Although not typically used to express the significance of a cluster solution, a coefficient of determination (R^2) can be developed for the matrix of data presented in Table 5.2. The R^2 value, in effect, represents the proportion of variance explained by using the cluster means rather than overall means for the entire sample. The R^2 developed by the five-cluster solution summarized in Table 5.1 is 0.55. This can be interpreted to mean that 55 percent of the variation in activity engagement across the sample is captured by the cluster means. The result is comparable to the findings of Pas (1982) who developed clusters of activity engagement for all age groups of the population. Pas developed solutions for 5 to 12 clusters which yielded R^2 values ranging from approximately 0.47 to 0.64, respectively. A more recent study by Principio and Pas (1996) developed clusters of <u>households</u> on the basis of time-use (percent of time engaged in six different classes of activities). Their final cluster solution resulted in an R^2 of approximately 0.77.

The R^2 value should be interpreted with caution when used as the sole criterion to assess the validity of a cluster solution. The value can be somewhat misleading because it places all importance on the variance of the data about the cluster means. While it provides a measure of the dispersion of the cluster data about the cluster centres, it does not ensure that the clusters are well separated and distinctive in character. For example, if a subgroup of data is closely grouped in Euclidean space and well separated from the remainder of the data set, then they likely represent a single contiguous partition. Although it would be most suitable to investigate the subgroup as a single cluster, the division of it into multiple clusters would yield a higher R^2 value thereby making the solution appear more significant.

The most appropriate procedure recommended by Aldenderfer and Blashfield (1984) to validate the clusters is to undertake significance tests on external variables, or variables *not* used to generate the cluster solution. The choice and relevance of the external variables are largely dependent on the final use of the stratification scheme. The general validity of the above cluster solution is tested in the following sections by illustrating the differences in travel behaviour and socio-demographics between the lifestyle clusters as defined by activity engagement.

5.1.2.1 Travel Behaviour of Activity Engagement Clusters

Table 5.3 summarizes the results of analysis of variance undertaken to examine the differences in travel behaviour variables for the five-cluster solution. As shown, there is a statistically significant difference between the lifestyle clusters in all but the mode split and trip duration variables. Note that trip duration only refers to the travel time to get to an activity. It is included as a proxy for travel distance which was not readily available through the data set. The total activities requiring travel and the number of trip tours have the largest corresponding F values indicative of the contrasting values between clusters. The respondent's role when in an automobile (i.e., as a driver or passenger), and the number of vehicle occupants are travel variables that are also statistically different between the clusters.

It is known from statistical theory that percentages or proportions form binomial rather than normal distributions. It was therefore necessary to manipulate the data variables describing 'role in auto' and 'mode split' to ensure a normal distribution (a necessary assumption of analysis of variance). An arcsine transformation was used to impose a normal distribution on these data (Zar, 1984). The square root of each proportion was transformed to its arcsine (i.e., the angle whose sine is the square root of p). For proportions of 0 to 1.0, the transformed values ranged between 0 and 90 degrees.

Members of the *Workers* cluster are shown to engage in the largest number of activities requiring travel, undertake the greatest number of subsequent trip tours, are most frequently the driver of an auto, the passenger of an auto the least, and carry the fewest passengers with them. In contrast, the *Relaxers* have opposite travel behaviour characteristics (i.e., they undertake the fewest activities requiring travel, the smallest number of trip tours, the least number of trips as driver, are the passenger of an auto the most, and average the greatest auto occupancy).

Figure 5.3 illustrates the travel needs for each cluster by plotting the mean number of activities reached by travel on a daily basis. This should not be confused with overall activity engagement (such as that presented in Table 5.2) which includes all activities despite whether travel outside the home is required or not. In the context of this study the term 'travel needs' should be considered synonymous with the pattern of activities that require travel. The daily engagement rate for each of the eight activity classes is depicted for the five clusters identified. Strikingly different travel patterns are evident between the five clusters. Analysis of variance on the engagement rates (average travel activities engaged in per day per person) shows that a statistically significant difference exists between the clusters for all eight activity classes. In fact, the differences are significant at the 0.001 level.

Table 5.3: Travel Behaviour Variable Means for Activity Engagement Clusters

Travel Variable	Activity Engagement Cluster						
	TV Viewers	Workers	Relaxers	Shoppers	Active Socializers	Entire Sample	F Statistic
Total Activities Requiring Travel	4.44	**7.65**	*3.64*	5.63	6.83	5.74	27.4*
Total Trip Tours	1.79	**2.78**	*1.53*	2.25	2.61	2.24	20.4*
Avg. Trip Duration (min.)	**23.5**	*19.3*	22.0	23.3	20.9	22.0	0.5
People in Auto	1.58	*1.39*	**1.82**	1.58	1.71	1.63	6.2*
Role in Auto:							
Driver (% of trips)	60.7	**78.1**	*49.7*	66.9	59.4	62.3	5.5*
Passenger (% of trips)	22.5	*11.5*	**38.3**	21.9	26.6	23.9	5.3*
Mode Split:							
Auto Trips (%)	*83.2*	**89.6**	88.0	88.7	86.0	86.2	1.4
Walk Trips (%)	**11.5**	*6.7*	7.5	7.1	9.8	9.4	1.7
Transit Trips (%)	**3.8**	3.6	*0.8*	2.8	3.3	3.2	0.4
Other Mode Trips (%)	1.4	*0.2*	**3.7**	1.4	0.9	1.2	1.2

* Statistically significant at the 0.05 significance level.

Note: **Bold** typeface indicates the **highest** mean for a particular travel variable.
Italics typeface indicates the *lowest* mean for a particular travel variable.

The number of travel activities per day used to determine the engagement rate was the number of times an activity type was listed in a respondent's daily itinerary. For example, an individual's itinerary of activities away from home might be: travel from home to work, travel to lunch, travel to shop, travel back to work, travel to home, travel to shop, travel to home. This itinerary represents two separate trip tours (recall that a trip tour begins and ends at home). The engagement rates for subsistence (work/school) and house maintenance (includes shopping) activities requiring travel would be 2 and the rate for meals would be 1.

It is interesting to contrast the travel needs depicted in Figure 5.3 with overall activity engagement as presented in Table 5.2. For example, it had been shown that *TV Viewers* spent an average of 16.9 hours (per two-day period) engaged in amusement type activities. However, it is shown that they only travel to engage in this activity 0.56 times, on average, each day. As noted previously, most of this activity is undertaken within the home. House maintenance is, in fact, the primary reason for trip-making among members of this cluster. *Shoppers*, and *Active Socializers* also have house maintenance as the primary travel need, while the remaining two clusters have this activity as their second most common reason to make a trip.

As expected, subsistence (work/school) is the primary travel need for the *Workers* cluster. They engage in this activity away from home 1.12 times per day, on average. Although this cluster had the second lowest overall engagement rate for meals (Table 5.2), it is shown that they reach this activity through travel more than any other cluster.

The *Active Socializers* were characterized by a large amount of time spent participating in social and amusement type activities (Table 5.2). However, as shown in Figure 5.3 these activities are only the third and fourth most common reasons for travel, following household maintenance and meals. It is shown that this cluster travels for meals nearly as often as the *Workers* which is in keeping with the characterization of this group.

A truly discretionary use of travel is to leave the home for a meal. There is a large contrast in the average number of times this activity is reached through travel by members of each of the different clusters. Daily engagement rates vary from as low as 0.25 for the *Relaxers*, to as high as 0.68 for the *Workers*.

Finally, it has been shown that the *Other* class of activities becomes a statistically significant variable between the clusters when individuals engage in it through travel. Recall from Table 4.1 that this class includes incidental, tag-along, and passenger pick-up and drop-off activities. This activity class had been shown not to vary significantly when travel was not a prerequisite.

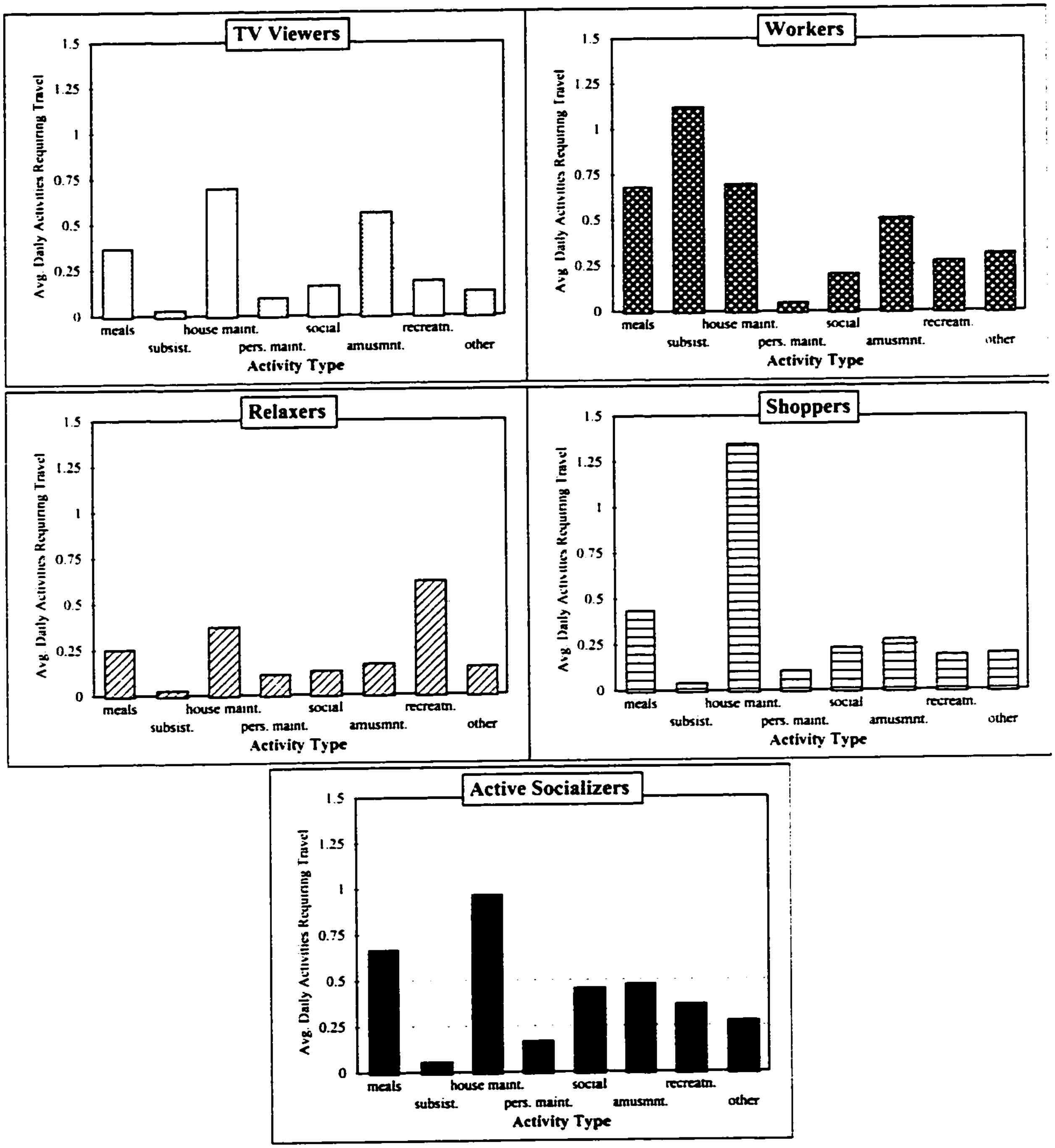

Figure 5.3: Daily Engagement Rates for Activities Requiring Travel (Activity Engagement Clusters)

5.1.2.2 Socio-demographic Characteristics of the Activity Engagement Clusters

A summary of analysis of variance results for the differences in socio-demographic variables between clusters is presented in Table 5.4. Since many variables are categorical, they could not be included in the analysis of variance tests. Alternatively, the categorical variables were subjected to standard chi-square tests to detect if there were statistically significant differences in the distributions of the response (socio-demographic) variables. The chi-square statistic was calculated and compared with tabulated values to decide whether the null hypothesis should be rejected. The null hypothesis assumed that there was no difference in the distribution of responses by the clusters and what would be expected given the overall sample response.

The data in Table 5.4 show that several variables are statistically different between the lifestyle groups defined by activity engagement including: age, employment, number of household vehicles, and the precent who are disabled enough to affect outside travel. Interestingly, the traditional travel forecasting variable of household size was found not to be significantly different between the clusters. Other key variables found not to be significantly different between clusters include gender, the percent who are licensed, race, proximity to the light rail system, and some household structural (relation to head of household) variables.

Some interesting and distinctive characteristics emerge for some activity engagement clusters. The *Workers* are shown to have the largest percentage of males, proportion with a driver's license, full and part-time workers, and the greatest average number of vehicles per household. Furthermore, they are the youngest of the clusters, and have the fewest who are retired, disabled, or whose relationship with the reported head of the household is that of parent (i.e., live with their offspring).

Many socio-demographic characteristics of the *Relaxers* are opposite to those found for the *Workers*. They are, on average, the oldest group and have the largest proportion who are the parents of the household head. However, the more significant findings for this group are that (1) nearly one-quarter have a disability significant enough to affect outside travel, (2) less than 73 percent are licensed to drive, and (3) they have the smallest proportion living in single family dwellings. Although not statistically significant, this group was also found to have the lowest mean income and largest household size. An overall characterization of this group might suggest that, as a whole, the members are mobility impaired, are often dependent on younger family members, and are less affluent. These socio-demographic characteristics have helped to explain the under involvement of this group in activities outside the home.

Table 5.4: Socio-demographic Variable Means for Activity Engagement Clusters

	Activity Engagement Cluster							
Socio-demographic Variable	TV Viewers	Workers	Relaxers	Shoppers	Active Socializers	Entire Sample	F Stat.	χ^2 Stat.
Age	74.1	*70.0*	**75.3**	72.4	73.3	73.2	10.3*	
Gender (% male)	45.2	**57.7**	42.5	45.5	*37.8*	43.3		7.4*
Household Size	*1.81*	1.85	**2.08**	1.91	1.84	1.86	2.1	
Relatn to House Head:								
% head	63.5	63.5	*54.8*	**65.2**	61.9	62.7		1.1
% spouse	*28.1*	**35.2**	30.1	29.9	32.9	30.9		2.1
% parent	5.5	*1.2*	**11.0**	3.6	3.8	4.5		12.0*
Home Type:								
% single fam.dwelling	79.7	84.7	*76.7*	**88.0**	76.8	80.4		2.7
% apartment	14.2	11.8	15.1	*7.1*	**16.8**	13.7		10.7*
%trailer/mobile	3.5	*1.2*	**5.5**	3.6	2.6	3.1		3.9
Household Income (x $1,000)	31.0	**37.2**	*30.4*	32.6	34.2	33.0	2.5*	
Employment:								
% full-time	*1.2*	**49.4**	2.7	2.2	2.4	5.5		298.1*
% part-time	*1.7*	**40.0**	2.7	4.5	4.0	6.0		183.2*
% homemaker	4.4	*0.0*	1.4	**5.4**	4.5	4.1		5.6
% retired	**90.7**	*10.6*	90.4	86.6	87.2	82.6		58.1*
Race:								
% Caucasian	95.9	*95.3*	**97.3**	96.9	96.9	96.5		0.1
% African-American	0.1	**1.2**	*0.0*	0.4	**1.2**	0.9		4.7
% other	3.2	**3.5**	2.7	2.7	*1.9*	2.6		1.8
Percent with License	80.9	**94.1**	*72.6*	89.3	87.7	85.5		5.0
Percent Handicapped	11.3	*0.0*	**24.7**	8.0	10.6	10.4		22.8*
Number of Vehicles	*1.49*	**1.75**	1.59	1.72	1.61	1.61	3.0*	
%Within ½-mile LRT	7.0	7.1	*6.9*	7.1	**9.2**	7.8		1.8

* Statistically significant at the 0.05 level.

Note: **Bold** typeface indicates the **highest** mean for a particular socio-demographic variable.
Italics typeface indicates the *lowest* mean for a particular socio-demographic variable.

The *TV Viewers* are shown to include the greatest proportion of retirees, and conversely, the smallest proportion of full or part-time workers. Furthermore, they own the fewest number of vehicles per household. This group is also somewhat mobility impaired given that more than 11 percent report a disability and that only about 81 percent are licensed to drive.

The only distinguishing socio-demographic characteristics of *Active Socializers* are that they have the largest proportion of females (more than 62 percent), and have the greatest propensity to live in an apartment. The *Shoppers* cluster, on the other hand, has the smallest percentage of members living in an apartment and the largest proportion who occupy a single family dwelling. They also have the second highest percentage of members who have a driver's license.

5.1.2.3 Stated-Adaptation Responses of the Activity Engagement Clusters

Results from part of the Stated-Adaptation survey were analyzed to detect if responses varied between the lifestyle groups developed based on activity engagement characteristics. The portion of the survey used was a road pricing questionnaire that targeted non-commute trips. Each respondent was reminded of a specific trip that they had reported as part of the activity-based travel survey. Depending on the characteristics of the specific trip (especially trip length and time of day) a series of eight pricing scenarios was presented to each respondent. The scenarios represented varying levels of either increased trip costs (through fuel taxes, tolls, transit fare, etc.), increased travel time, or both. Furthermore, each pricing scenario had several modal alternatives, with associated time and financial costs, to make the same trip. The respondents were given seven adaptation possibilities if the proposed travel conditions persisted for several years. These adaptation options include:

(1) Make trip less often.
(2) Combine trip with other trips.
(3) Make same trip at different time of day.
(4) Look for similar destination closer to home.
(5) Do activity at home.
(6) Not make trip at all.
(7) None of the above.

Unfortunately, the response rate of the stated-adaptation survey was much lower than the activity survey. Only 64 elderly people completed the road pricing portion of the stated-adaptation survey. However, each respondent indicated their expected adaptation behaviour to each of the eight pricing scenarios resulting in 512 observations. Caution must be exercised when interpreting these results since they represent *stated* adaptation and may not necessarily reflect the respondent's actual modification behaviour. The results are presented in Table 5.5.

None of the adaptation responses were found to vary statistically between the five-clusters. A larger sample size is required to further explore whether there are, in fact, significant differences. Nevertheless, the data do provide an indication of the preferred adaptive behaviours that may exist within the clusters (i.e., scrutinizing the columns of the table). For example, the *Relaxers* prefer to adapt by 'not making the trip at all' when faced with increased travel costs or trip times. Conversely, the *TV Viewers*, *Shoppers*, and *Active Socializers* all prefer to adapt by 'combining the trip with others', and have a low likelihood of resorting to 'not making the trip at all'. The *Workers* (keeping in mind that the survey dealt explicitly with non-commute trips) are shown to prefer to 'make the trip less often', and have the greatest response among the groups to 'make the trip at a different time of day'.

Table 5.5: Non-Commute Stated-Adaptation Responses for Activity Engagement Clusters

Stated-Adaptation Response	Activity Engagement Cluster (average number of times chosen for the 8 scenarios)						
	TV Viewers	Workers	Relaxers	Shoppers	Active Socializers	Entire Sample	F Stat. *
make trip less often	3.0	4.2	*0.0*	**4.5**	3.1	3.4	1.5
combine trip with others	3.8	3.2	*0.0*	**4.8**	3.6	3.8	1.2
make trip at different time of day	0.4	3.0	*0.0*	**1.8**	0.9	1.0	1.8
look for similar destination closer to home	**3.0**	*0.8*	**3.0**	1.3	2.4	2.2	1.0
do activity at home	0.1	**1.8**	*0.0*	0.8	0.6	0.5	1.1
not make trip at all	*1.0*	1.8	**4.0**	1.1	1.0	1.2	1.0
none of the above	1.5	*0.2*	**3.5**	0.9	0.6	1.0	1.7

* None are statistically significant at the 0.05 level.

Note: **Bold** typeface indicates the **highest** mean for a particular adaptation response.
Italics typeface indicates the *lowest* mean for a particular adaptation response.

5.2 Cluster Analysis Based on Socio-demographic Characteristics

Following a similar approach to that used in section 5.1, lifestyle clusters were developed based solely on socio-demographic characteristics of the elderly. Variables used as dimensions to define the cluster groups included: age, the total number of vehicles owned by a household, total household income, household size, gender, possession of a driver's license, presence of a disability significant enough to affect travel outside the home, relationship to the household head, and employment.

A correlation analysis was done on the variables before cluster analyses were undertaken. If two variables were highly correlated (coefficient of 0.80 or higher), one was removed as a defining dimension for the clusters. Home type was not included as a cluster dimension given its high correlation with household income. Furthermore, some variables such as race and proximity to the light rail transit system were excluded from the final analyses since they did not contribute to the formation of clusters.

The combination of variables used was primarily dictated by those that were available through the Oregon/Southwest Washington survey. Since some socio-demographic variables describe mobility characteristics (e.g., number of vehicles, presence of driver's license, and disability affecting travel) the clusters developed through this analysis were correspondingly biased in this respect. Undoubtedly, different groupings would result if more social, economic and demographic information were available. Nevertheless, for the purposes of the travel model under development, these dimensions governing cluster membership are appropriate.

A comprehensive series of preliminary cluster analyses were undertaken to develop the final cluster solution. These preliminary analyses followed the same patterns and techniques as those presented in section 5.1.1. An additional difficulty encountered when manipulating the socio-demographic variables was the need to include both quantitative and categorical data. The previous clustering exercise based on activity engagement was simplified since it was based on eight activity variables that all had the same quantitative units of measure. The existence of categorical observations (e.g., gender, relation to household head, etc.), besides different quantitative units of measure (e.g., age in years, and income in dollars, etc.), required the data to be standardized before the application of any clustering algorithm. Transformation of the data to a standard ensures that the effect of each variable on cluster formation is equalized. Although quantitative and qualitative variables are not commonly combined in cluster analyses, it was felt that for the purposes of this research the contribution of all of the above variables should be understood. To include both types of data the quantitative variables were standardized to a range of 0 to 1, and the qualitative variables converted to a binary format. In this way, no one variable could contribute disproportionately to the development of cluster boundaries.

Figures 5.4 and 5.5 were developed through preliminary analyses to provide a better understanding of the contribution of increasing numbers of clusters to the explanation of variance in the socio-demographic dimensions. Again, these plots were developed without the benefit of establishing cluster centres using a hierarchical clustering technique. The figures illustrate that the incremental explanation of variance is greatly reduced beyond about a six or seven-cluster solution. A range of solutions involving four to eight clusters was selected for more detailed analyses.

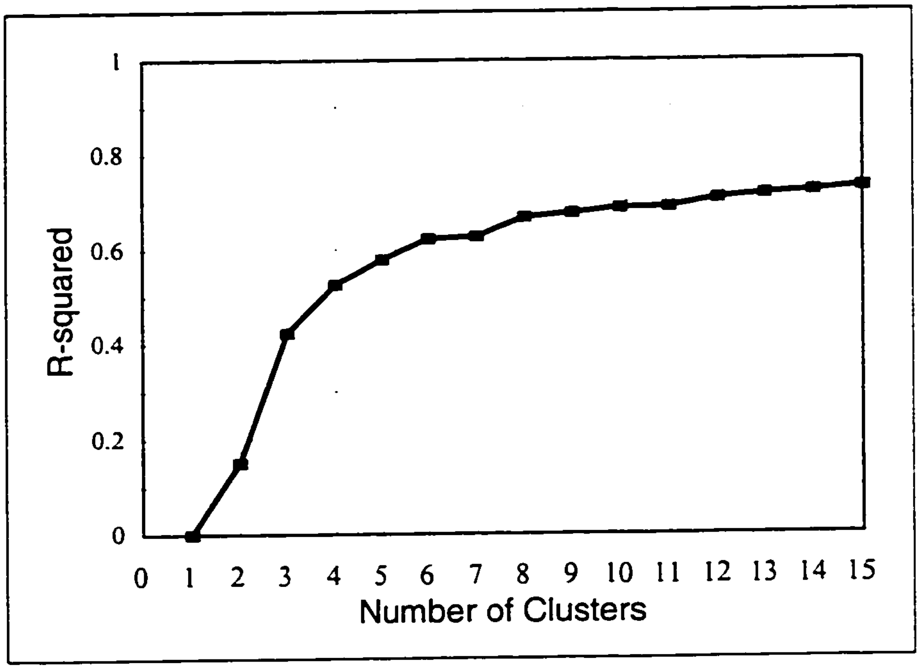

Figure 5.4: R^2 Relationship With Number of Clusters (Socio-demographic Clusters)

A sample of 250 cases was randomly selected from the data and subjected to hierarchical cluster analyses to develop initial cluster centres as a seed for the K-means technique. The initial cluster centres were developed for the established range of four to eight clusters. Ultimately, a six-cluster solution was found to provide the optimal segregation of the data. Again, at this stage, the primary selection criterion was the size of clusters. Solutions with more clusters resulted in groupings that were either too small to be statistically significant or difficult to distinguish or interpret. Alternatively, solutions with fewer clusters tended to form one or two very large groups with relatively heterogeneous characteristics, while the remaining clusters had unique characteristics but small memberships.

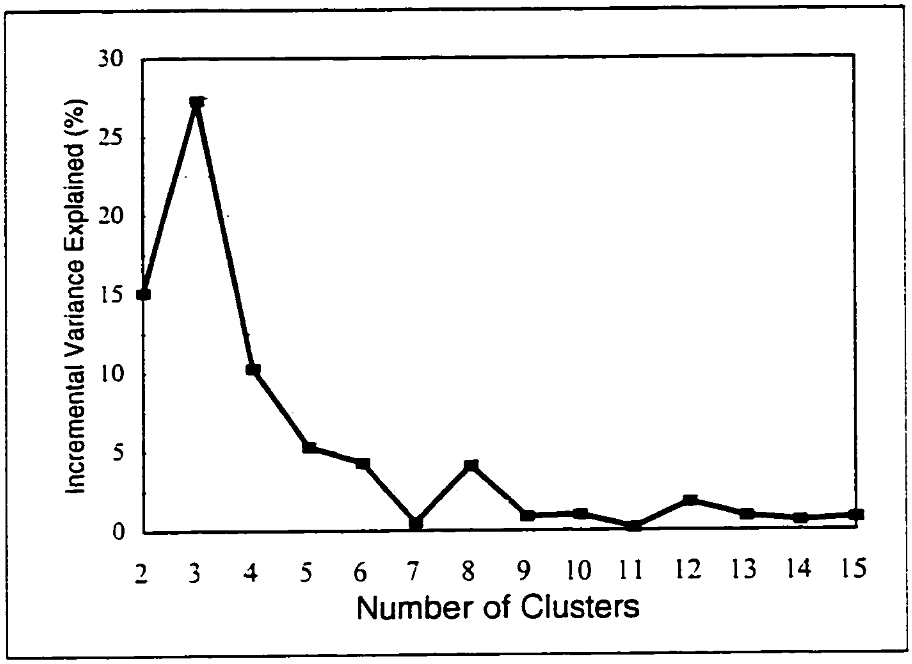

Figure 5.5: Incremental Information Explained With Increasing Number of Clusters (Socio-demographic Clusters)

The R^2 developed by the final solution was determined to be 0.623. Again, this value indicates that by segregating the elderly into subgroups, the respective cluster means explain 62.3 percent of the variance in the socio-demographic variables used for cluster dimensions.

5.2.1 Description of Socio-demographic Clusters

Table 5.6 presents the final groupings developed based on socio-demographic characteristics of the survey respondents. The clusters range in size from 50 to 436 representing approximately 4 to 38 percent of the entire sample, respectively. As previously discussed, more equalized cluster sizes were not attainable given the characteristics of the data. Again, the clusters are given descriptive labels that characterize their dominant attributes.

Table 5.6: Distribution of Survey Respondents Across Socio-demographic Clusters

#	Cluster Label	Cluster Size	Percent of Sample
1	Workers	125	10.9
2	Mobile Widows	337	29.3
3	Granny Flats	50	4.3
4	Mobility Impaired	141	12.2
5	Affluent Males	436	37.9
6	Disabled Drivers	61	5.3
	Entire Sample	1150	100.0

Table 5.7 presents the cluster means of the socio-demographic variables developed through the analyses. The cluster means provide the ability to interpret the dominant characteristics of each group. All variables used to delineate cluster membership are shown to have statistically significant differences between the six groupings. The F statistics (and chi-square statistics for categorical data) are reported to be significant at the 5 percent level when, in fact, they are significant even below the 1 percent level.

The *Workers* cluster is so named because all of its members continue to be employed either full or part-time. The group has the youngest average age. Perhaps surprisingly, more than 39 percent of the group are female and only 62 percent are listed as the head of their respective households. Nearly 97 percent of the cluster members are licensed to drive an automobile.

Mobile Widows is a cluster whose membership is almost exclusively female (99.4 percent), most of whom live alone or are the household heads. The members have the second lowest average income, however, all maintain a driver's license. All of those who belong to the *Granny Flats* cluster live with their children, resulting in the group with the largest average household size and income. Most are female (80 percent), oldest on average, more than one-third disabled, very few are employed, and only 48 percent are licensed to drive. Such characteristics would imply that members of this cluster rely on others for at least some of their transportation needs.

Table 5.7: Socio-demographic Cluster Means

Socio-demographic Variable	Socio-demographic Cluster								
	Workers	Mobile Widows	Granny Flats	Mobility Impaired	Affluent Males	Disabled Drivers	Entire Sample	F Stat.	χ^2 Stat.
Age	*69.7*	72.8	**78.0**	77.8	72.3	74.7	73.2	35.0*	
Hshld. Vehicles	1.90	1.41	**2.18**	*0.63*	1.93	1.54	1.61	71.6*	
Hshld. Income (x $1,000)	37.6	27.6	**42.3**	24.7	38.1	*24.4*	33.0	25.3*	
Househld Size	1.86	*1.58*	**3.26**	1.63	2.02	1.74	1.86	60.3*	
Gender (%male)	60.8	*0.6*	20.0	22.7	**81.4**	37.7	43.3		317.5*
Licensed (%)	96.9	**100.0**	48.0	*0.0*	**100.0**	**100.0**	85.5		151.8*
Handicapped (%)	1.6	*0.0*	36.0	27.7	*0.0*	**100.0**	10.4		665.7*
Head of Household (%)	62.4	**92.6**	*0.0*	66.0	45.6	63.9	62.7		99.7*
Parent of Househld Head (%)	1.6	*0.0*	**100.0**	*0.0*	*0.0*	*0.0*	4.5		1198.7*
Employed (%)	**100.0**	*0.0*	2.0	4.3	*0.0*	*0.0*	11.5		986.5*

* Statistically significant at the 0.05 significance level.

Note: **Bold** typeface indicates the **highest** mean for a particular socio-demographic variable.
Italics typeface indicates the *lowest* mean for a particular socio-demographic variable.

The *Mobility Impaired* cluster is characterized by members who collectively have the second oldest average age, only 0.63 vehicles per household, more than 77 percent are female, more than one-quarter are disabled, and none hold a driver's license. These attributes suggest that this group is also highly dependent on spouses, relatives, friends, or public services for their travel needs.

More than 81 percent of the members of the *Affluent Males* cluster are male. Cluster members are on average the second youngest, have the second highest income, no incidence of disability, and all hold a valid driver's license. Furthermore, none reside with their offspring, and they have the second highest vehicle ownership. These indicators suggest that this cluster represents an independent and mobile membership.

Those belonging to the *Disabled Drivers* cluster all maintain a driver's license yet everyone reports a disability significant enough to affect outside travel. The group is nearly two-thirds female, slightly older than average, with no members who are employed.

5.2.1.1 Activity Engagement of the Socio-demographic Clusters

The mean hours that members of the socio-demographic clusters participate in each of the eight activity classes are presented in Table 5.8. As shown, all but one of the eight activity classes show statistically significant variations between the six clusters. Resulting from most of the elderly who are still employed being combined in the *Workers* group, the subsistence class of activities is the most strongly discriminated variable between the clusters.

Table 5.8: Activity Engagement for Socio-demographic Clusters

Activity Type	Socio-demographic Cluster (mean participation over 2-day period: hours)							
	Workers	Mobile Widows	Granny Flats	Mobility Impaired	Affluent Males	Disabled Drivers	Entire Sample	F Statistic
Meals	*3.4*	**4.3**	3.5	4.0	3.8	3.8	3.9	4.2*
Work/school	**7.9**	0.3	0.5	0.5	0.2	*0.0*	1.1	232.1*
House Maintenance	*4.0*	**6.2**	4.4	4.1	5.8	5.1	5.4	7.8*
Personal Maintenance	*0.1*	0.4	**0.7**	0.2	0.4	0.5	0.3	1.7
Social	1.3	**2.2**	*0.8*	2.1	**2.2**	1.5	2.0	3.0*
Amusement	*7.1*	9.8	11.2	**11.6**	10.3	10.6	10.0	9.9*
Recreation	*1.8*	2.3	**4.7**	3.5	2.5	3.8	2.6	5.7*
Other	**0.2**	*0.1*	*0.1*	*0.1*	**0.2**	*0.1*	0.2	2.5*

* Statistically significant at the 0.05 significance level.

Note: **Bold** typeface indicates the **highest** mean for a particular activity type.
Italics typeface indicates the *lowest* mean for a particular activity type.

Not surprisingly, the clusters that have mobility restrictions (*Granny Flats*, *Mobility Impaired* and *Disabled Drivers)* engage in amusement activities more often. Recall that this class of activities tends to be dominated by the specific activity of 'in-home amusement'.

The *Mobile Widows* spend the most time engaged in house maintenance activities which are dominated by the 'general shopping' activity. It is interesting that the *Workers* participate the least in five of seven activities other than subsistence.

Although significant differences between the clusters are shown for seven of the eight activity types, the differences are not as strong as those developed for the activity engagement clusters (Table 5.2). This result is expected given the basis for delineation. Both approaches have identified a group of workers. It appears, however, that the socio-demographic cluster of workers includes more part-time employees given the larger membership (129 versus 85 for the activity engagement cluster) and the lower average participation (7.9 hours per 2-day period).

5.2.1.2 Travel Behaviour of the Socio-demographic Clusters

The travel behaviour variables presented in Table 5.9 also show strong overall variations between the clusters defined based on socio-demographic variables. All travel variables exhibit a statistically significant variation between the six clusters. Most important, both the total number of trip tours and the number of activities reached by travel are strongly discriminated between the groups.

Interestingly, trip duration is found to vary from a low average of about 14 minutes for those belonging to the *Granny Flats* to a high that is nearly double for the *Affluent Males* cluster. If trip duration is used as a proxy for distance, the findings suggest that some groups tend to stay much closer to home than others.

The average auto occupancy for those in the *Mobility Impaired* and *Granny Flats* clusters is higher than any of the other groups. This corresponds with the fact that few in these clusters are licensed to drive. Those in the *Mobility Impaired* group make the fewest auto trips, yet when they do they almost never drive. Furthermore, they rely on either walking or the transit system much more than any of the other clusters.

Table 5.9: Travel Behaviour Variable Means for Socio-demographic Clusters

Travel Variable	Socio-demographic Cluster: Workers	Mobile Widows	Granny Flats	Mobility Impaired	Affluent Males	Disabled Drivers	Entire Sample	F Statistic
Total Activities Requiring Travel	**7.74**	6.21	*2.94*	3.45	6.03	4.51	5.74	23.6*
Total Trip Tours	**2.89**	2.36	*1.18*	1.37	2.44	1.64	2.24	22.9*
Avg. Trip Duration (min.)	20.18	18.96	*14.11*	21.34	**26.16**	17.94	22.00	2.3*
People in Auto	*1.34*	1.53	2.14	**2.34**	1.63	1.68	1.63	30.8*
Role in Auto:								
Driver (% of trips)	**83.9**	62.0	22.7	*2.6*	75.0	54.6	62.3	87.9*
Passenger (% of trips)	*9.3*	25.6	**54.0**	53.2	15.7	37.8	23.9	28.9*
Mode Split:								
Auto Trips (%)	**93.2**	87.6	76.8	*55.8*	90.6	92.4	86.2	30.5*
Walk Trips (%)	*5.5*	9.2	16.0	**24.4**	6.7	6.4	9.4	11.3*
Transit Trips (%)	1.3	2.2	1.7	**16.5**	1.7	*0.6*	3.2	22.1*
Other Mode Trips (%)	*0.1*	1.0	**5.6**	3.4	1.0	0.7	1.2	2.7*

* Statistically significant at the 0.05 significance level.
Note: **Bold** typeface indicates the **highest** mean for a particular travel variable.
Italics typeface indicates the *lowest* mean for a particular travel variable.

A significant finding shows that those belonging to the *Disabled Drivers* cluster rely on the auto for more than 92 percent of their trips yet all are disabled. Furthermore, they use the transit system and walk the least of any other cluster. This identifies a segment among the elderly who seem to have some very specific travel needs.

The findings presented in Table 5.9 demonstrate that by segregating the elderly population into clusters based on key socio-demographic variables, distinct travel behaviour can be associated with each group. Interestingly, the socio-demographic clusters were able to provide substantial differences in some key travel behaviour variables that the clusters based on activity engagement (Table 5.3) could not. Trip duration and all mode choice variables varied significantly between the socio-demographic clusters, while they were found not to be significantly different between the activity engagement clusters.

Since travel behaviour is considered the result of servicing travel needs (or activity engagement) the next step was to understand if, in fact, these needs varied between the clusters. Figure 5.6 illustrates the underlying reasons for travel among the six clusters identified. The patterns of daily activities that require travel are presented for each cluster. The levels of daily engagement for all but one activity class

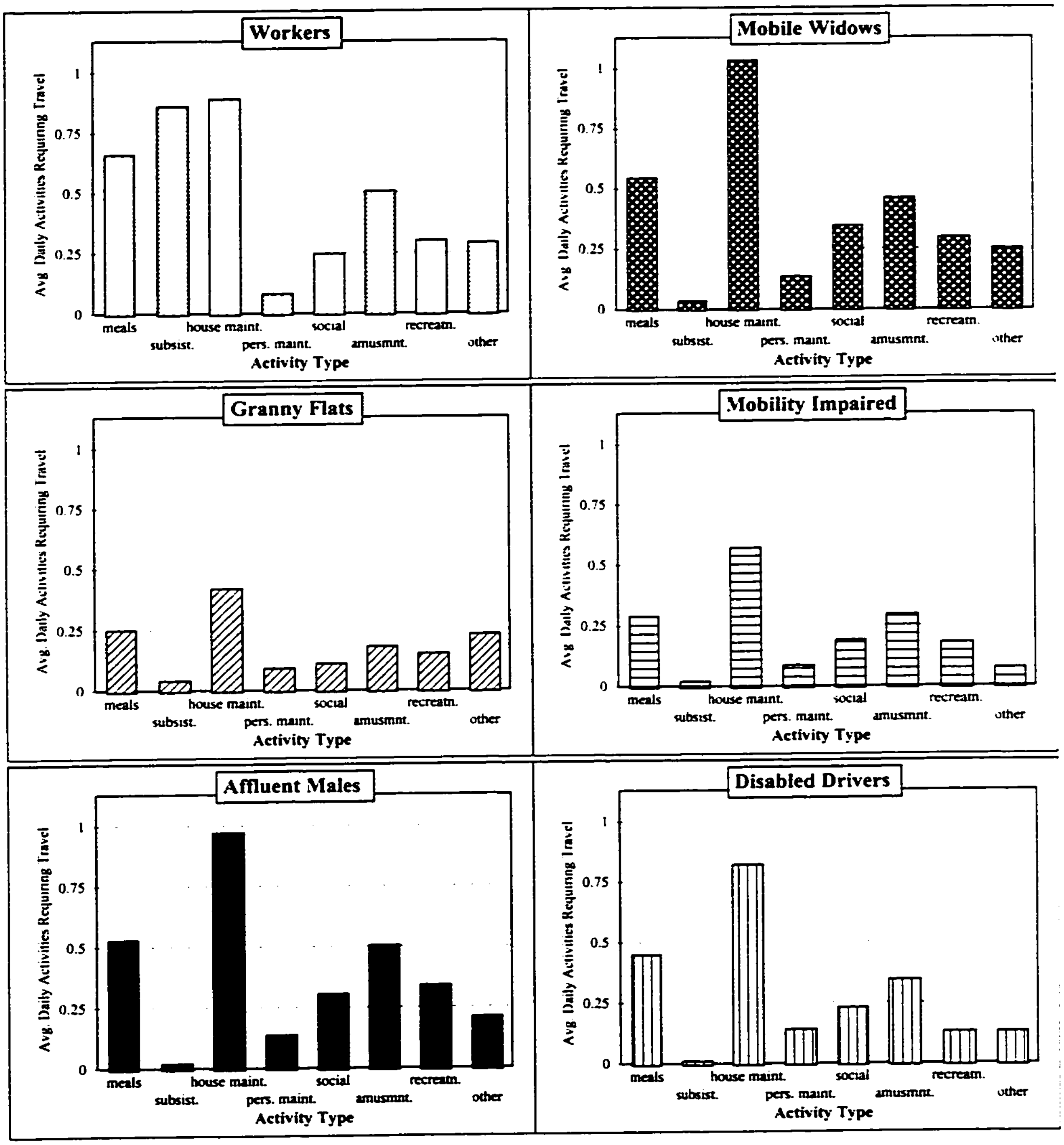

Figure 5.6: Daily Engagement Rates for Activities Requiring Travel (Socio-demographic Clusters)

were found to have significant variation between the clusters at a significance level below 1 percent. The 'personal maintenance' activity class does not show a statistically significant variation between the clusters.

Most notable is the importance of 'house maintenance' activities among all clusters. Although the frequency of engagement changes from group to group, it is the dominant reason for travel. Recall that 'general shopping' is the primary activity within this category.

The overall patterns for the *Mobile Widows, Mobility Impaired, Affluent Males,* and *Disabled Drivers* are somewhat similar in that meals and amusement are either the second or third most common reason for travel. Nevertheless, the frequency rate of engagement varies significantly from group to group.

5.2.1.3 Stated-Adaptation Responses of the Socio-demographic Clusters

The stated-adaptation responses to the road pricing survey were examined for each of the six socio-demographic clusters. The results are depicted in Table 5.10. Again, because of the small sample of responses to this component of the survey only one adaptation, to 'make trip less often', was significantly different between the clusters. However, the 'none of the above' response (likely indicative of no adaptation) also varied significantly between the clusters. Nevertheless, the data do illustrate that each cluster has favoured responses to increased price or congestion levels. For example, it is interesting that the most common adaptation among members of the *Mobility Impaired* group is to 'not make the trip at all', while this is one of the least desirable options among the other clusters. This could be construed as an indication that this group is elastic to changes in transportation attributes. Although the variability of different adaptation responses between the clusters cannot be shown with the limited amount of data, there appear to be distinct differences in adaptation preferences within the groups.

5.3 Cluster Analysis Based on Travel Behaviour

The final approach used to cluster analyse the data for elderly respondents employed travel behaviour variables to define the dimensions of the clusters. The premise underlying this perspective was that people with similar travel behaviours may have common reasons (or activity patterns) for trip-making, and similar socio-demographic characteristics.

Table 5.10: Non-Commute Stated-Adaptation Responses for Socio-demographic Clusters

	Socio-demographic Cluster (average number of times chosen for the 8 scenarios)							
Stated-Adaptation Response	Workers	Mobile Widows	Granny Flats	Mobility Impaired	Affluent Males	Disabled Drivers	Entire Sample	F Statistic
make trip less often	3.2	**4.4**	---	2.5	2.7	*0.3*	3.4	2.5*
combine with others	4.2	**4.6**	---	*0.0*	3.1	3.3	3.8	1.4
make trip at different time of day	**1.9**	0.8	---	*0.0*	1.4	*0.0*	1.0	0.7
look for similar destination closer to home	1.5	2.8	---	*0.0*	1.7	**3.0**	2.2	0.9
do activity at home	**1.5**	0.4	---	*0.0*	0.5	*0.0*	0.5	0.9
not make trip at all	1.5	1.2	---	*0.0*	0.9	**3.3**	1.2	1.0
none of the above	0.4	0.4	---	**5.0**	1.8	*0.0*	1.0	5.4*

* Statistically significant at the 0.05 significance level.
Note: **Bold** typeface indicates the **highest** mean for a particular adaptation response.
Italics typeface indicates the *lowest* mean for a particular adaptation response.

The variables used to define the cluster groups included: the number of trip tours (two-day totals), trip duration, auto occupancy, role in auto (percent of time as the driver), and mode split (auto, walk, transit, and other mode). Again, a correlation analysis was done on the variables before cluster analyses were undertaken. The total number of activities requiring travel was removed given its high correlation with the total number of trip tours. Similarly, the percent of trips as a passenger, and all modes other than auto were removed from the analyses. It should be noted that these variables are still important attributes of one's travel characteristics; however, their use as a cluster dimension would result in undue emphasis being assigned to a particular aspect of travel behaviour.

Since all variables included have quantitative measures, the data could be standardized using traditional Z-scores before cluster analyses were initiated. This transformed all variable measures to a mean of zero and standard deviation of one. As previously noted, standardization ensures that the effect of each variable on cluster formation is equalized.

Preliminary analyses designed to establish a range of clusters to be considered for more detailed investigation produced the data depicted in Figures 5.7 and 5.8. Again, these plots were developed

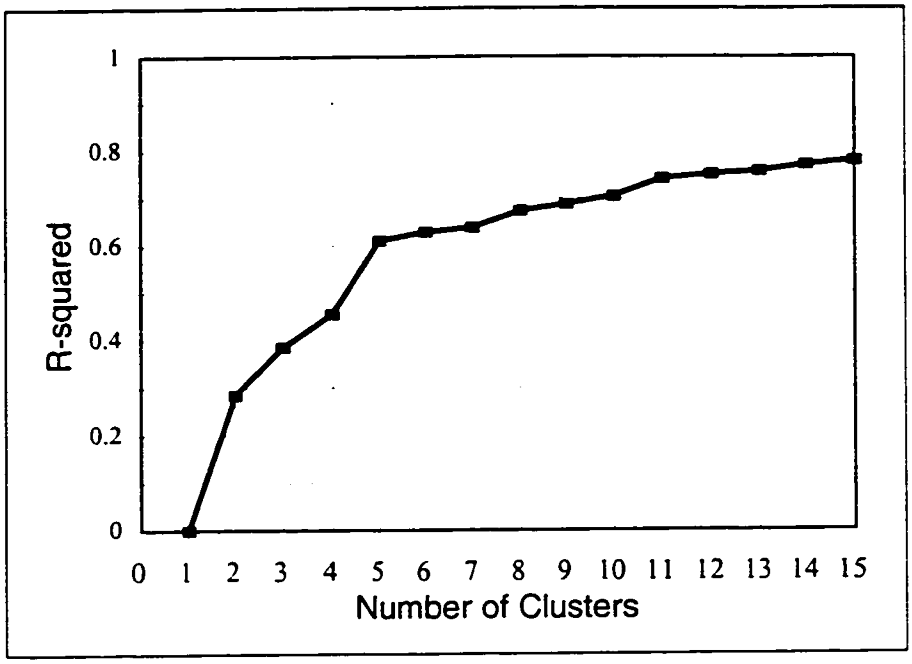

Figure 5.7: R^2 Relationship With Number of Clusters (Travel Behaviour Clusters)

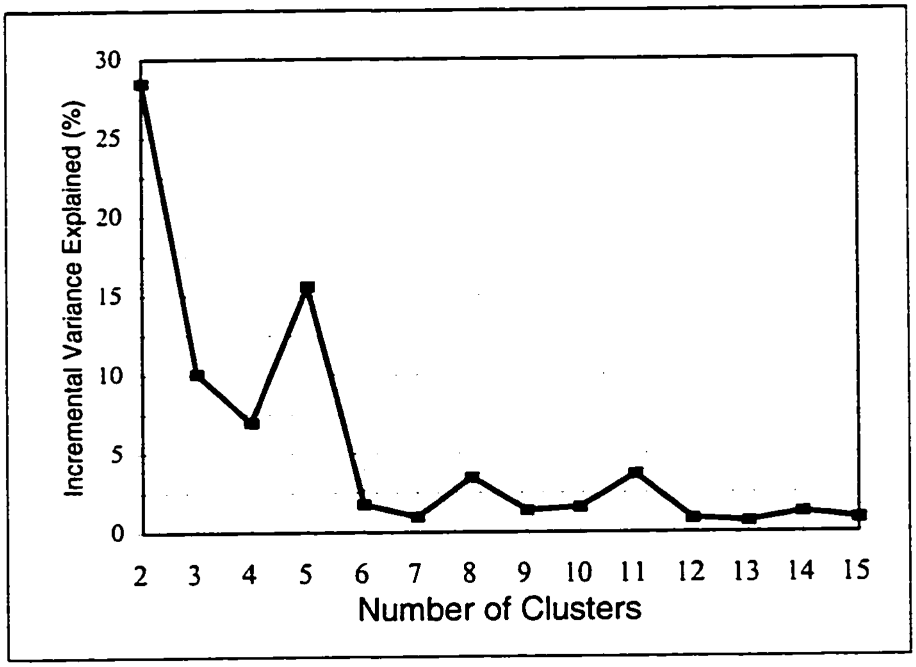

Figure 5.8: Incremental Information Explained With Increasing Number of Clusters (Travel Behaviour Clusters)

without the benefit of estimating initial cluster centres using hierarchical clustering techniques. It is shown that there is a marked reduction in the incremental variance being explained by additional clusters beyond a six-cluster solution. Note that these data do not include 160 respondents who did not travel during the two-day survey period. A range of four to seven clusters was delineated for more detailed analysis.

A random sample of 250 cases was drawn from the entire data set and subjected to a series of hierarchical cluster analyses to establish the initial cluster centres for four to seven cluster solutions to be used by the K-means technique. Those not travelling were aggregated as a separate cluster. The analyses found that a further six groups based on travel behaviour variables provided an optimal solution, in effect, providing a seven-cluster solution. Again, the sizes of clusters played a vital role in selecting the final solution. Those solutions with fewer than six clusters had at least one cluster with more than 500 respondents, while solutions with more had at least one cluster with less than 50 observations.

An R^2 of 0.63 was developed by the final cluster scheme. This can be interpreted that the cluster means can capture 63 percent of the variation in the travel behaviour variables (used as cluster dimensions) compared to using overall sample means.

5.3.1 Description of Travel Behaviour Clusters

Table 5.11 presents the final groupings developed based on travel behaviour characteristics of the survey respondents. As shown, the clusters range in size from 41 to 394, or 3.6 to 34.2 percent of the entire sample, respectively. Again, the clusters were subjectively assigned descriptive labels based on their dominant characteristics.

Table 5.12 lists the cluster means of the travel behaviour variables for the final solution. The variables removed from the cluster analysis based on correlation are presented as well to form a complete description of the travel characteristics of the groups. All F values are statistically significant indicative that the clusters are discriminatory (significantly different) across each variable.

Members of the first cluster *Transit / Walkers* engage in walking or transit trips more than any other group. In fact, less than 11 percent of their trips are made by auto compared with an overall sample average of 86.2 percent. It is also noteworthy that only 1.5 percent of trips are made by group members as the driver of an auto.

Table 5.11: Distribution of Survey Respondents Across Travel Behaviour Clusters

#	Cluster Label	Cluster Size	Percent of Sample
1	Transit / Walkers	89	7.7
2	Frequent Local Drivers	171	14.9
3	Infrequent Local Drivers	394	34.2
4	Walkers / Drivers	91	7.9
5	Adventurers	41	3.6
6	Auto Passengers	204	17.7
7	Homebodies	160	13.9
	Entire Sample	1150	100.0

The *Frequent Local Drivers* cluster is characterized by members who have the highest trip rate among all groups. The number of activities that they travel to is double the overall average. Furthermore, their average trip duration (travel time) is relatively short compared with other groups. The automobile dominates their modal choice. The *Infrequent Local Drivers* group has similar characteristics, however, they only average one trip tour per day to reach half as many activities. This group relies on the auto for nearly all trips outside the home.

More than 30 percent of all trips made by the *Walkers / Drivers* are made on foot. Furthermore, members have a slightly above average trip tour rate. It seems that this group maintains a physically active lifestyle besides the continuance of driving habits.

Adventurers take the fewest trips (excluding those who took no trips during the survey period) and go to the fewest activities, yet when they do travel, trip times are much greater than any other group. The auto dominates their modal choice.

Those who belong to the *Auto Passengers* cluster make trips as passengers nearly 88 percent of the time. It is quite possible that many members of this group could belong to the same household as members of the *Frequent* or *Infrequent Local Driver* clusters.

Table 5.12: Travel Behaviour Cluster Means

	Travel Behaviour Cluster								
Travel Variable	Trnst./ Walker	Freq. Local Driver	Infreq. Local Driver	Walker/ Driver	Advnt.	Auto Pass.	Home-Bodies	Entire Sample	F Statistic‡
Total Activities Requiring Travel †	4.73	**11.47**	5.65	7.44	3.83	5.65	*0.00*	5.74	259.3*
Total Trip Tours	1.99	**4.78**	1.98	3.20	1.71	2.12	*0.00*	2.24	456.7*
Avg. Trip Duration (min.)	23.5	16.9	*16.1*	20.2	**70.7**	18.8	---	22.0	1423.3*
People in Auto	**2.27**	1.50	*1.34*	1.38	1.82	2.26	---	1.63	91.1*
Role in Auto:									
Driver (% of trips)	*1.5*	84.4	**94.7**	57.6	67.3	8.3	---	62.3	757.1*
Passenger † (% of trips)	9.3	8.9	*4.6*	6.2	27.1	**87.8**	---	23.9	504.5*
Mode Split:									
Auto Trips (%)	*10.8*	93.9	**99.2**	63.8	94.4	96.0	---	86.2	812.0*
Walk Trips (%) †	**49.6**	6.0	*0.7*	30.6	1.2	3.7	---	9.4	164.0*
Transit Trips (%) †	**30.5**	0.4	*0.0*	3.7	1.2	0.3	---	3.2	97.0*
Other Trips (%) †	**9.1**	0.4	*0.0*	1.9	3.1	*0.0*	---	1.2	14.5*

‡ Exclusive of *Homebodies* cluster.
† Variable was not used as a cluster dimension due to correlation with other travel variables.
* Statistically significant at the 0.05 significance level.
Note: **Bold** typeface indicates the **highest** mean for a particular travel variable.
Italics typeface indicates the *lowest* mean for a particular travel variable.

Finally, those who did not report any travel outside the home over the two-day survey period, are included in the *Homebodies* cluster. Subsequent analyses that follow showed that this group does, in fact, have distinguishing characteristics.

The travel behaviour clusters were able to provide much stronger delineations in the travel variables than the other two cluster approaches (i.e., activity engagement and socio-demographic clusters). The corresponding F statistics can be compared between Tables 5.3, 5.9, and 5.12. Again, this is expected given the basis for cluster formation.

Although the clusters based on travel behaviour characteristics were found to discriminate on these variables, the underlying reasons for travel are less distinctive. Figure 5.9 depicts the activities for which

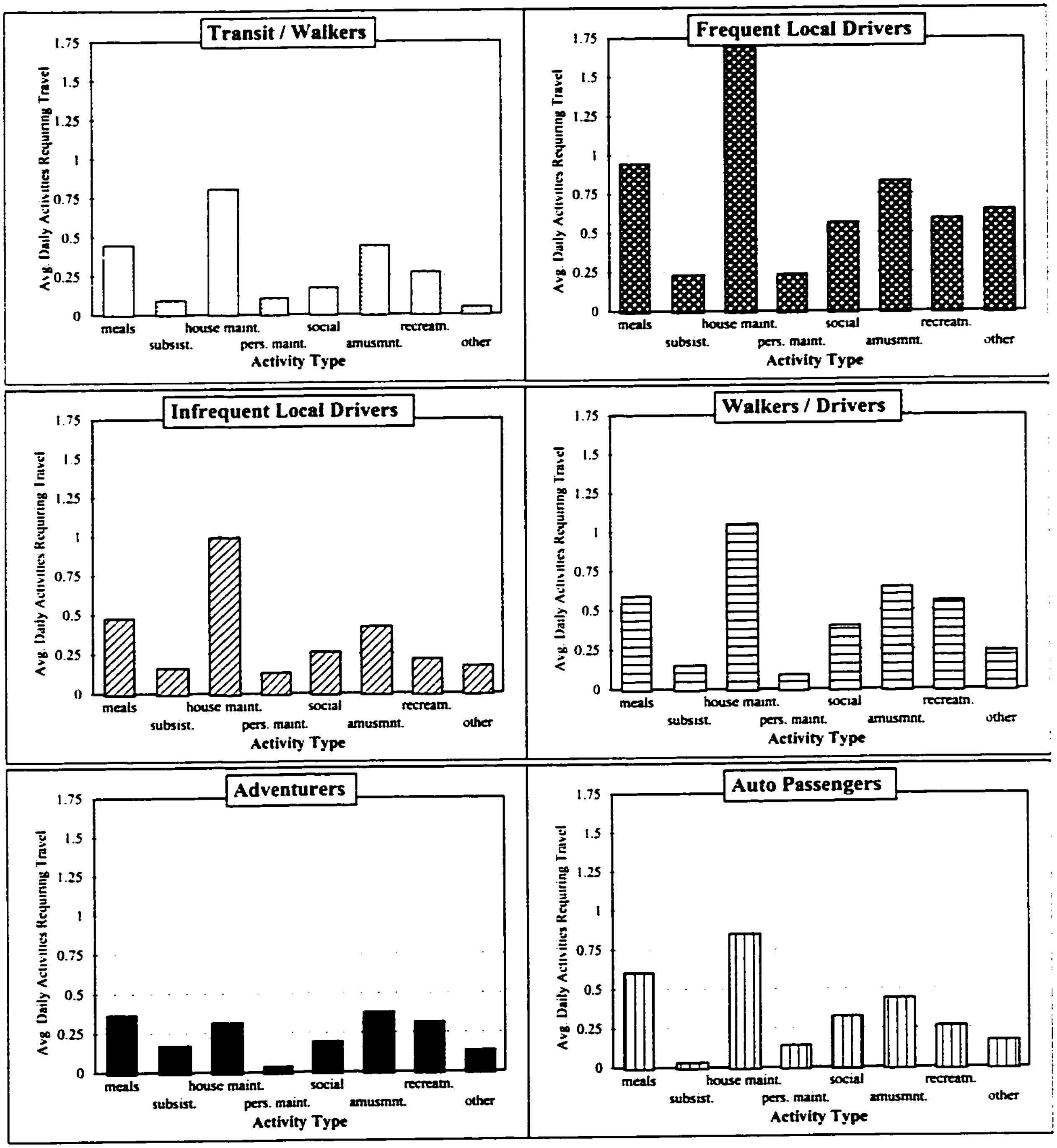

Figure 5.9: Daily Engagement Rates for Activities Requiring Travel (Travel Behaviour Clusters)

Note: members of the *Homebodies* cluster did not travel during the survey period.

travel is required for each cluster. It is shown that similar patterns exist for four of the clusters including *Transit / Walkers, Infrequent Local Drivers, Walkers / Drivers,* and *Auto Passengers*. The pattern is also similar for *Frequent Local Drivers*, although the frequencies of activity engagement are consistently higher. Not surprisingly, members of the *Adventurers* cluster travel disproportionately more often than other groups to engage in amusement and recreational activities. They also make trips for household maintenance reasons disproportionately less than any of the other clusters.

5.3.1.1 Activity Engagement of the Travel Behaviour Clusters

Average activity engagement rates for members of the travel behaviour clusters are presented in Table 5.13. Recall that these values represent all activities despite whether travel is necessary. Only six of the eight activity classes show statistically significant variations between the seven clusters. Personal maintenance and social activities were found to have no significant variations between the clusters. Although overall differences exist, there are few substantial variations in overall patterns between the groups. The differences are generally not as significant as those developed by the socio-demographic clusters (Table 5.8), and are much less significant than those of the activity engagement clusters (Table 5.2).

Table 5.13: Activity Engagement for Travel Behaviour Clusters

	Travel Behaviour Cluster (mean participation over 2-day period; hours)								
Activity Type	Trnst/ Walker	Freq. Local Driver	Infreq. Local Driver	Walker/ Driver	Advent	Auto Pass.	Home-Bodies	Entire Sample	F Statistic
Meals	**4.2**	3.8	3.8	3.9	*3.0*	**4.2**	3.8	3.9	2.4*
Work/school	1.1	1.5	**1.7**	1.0	1.1	0.5	*0.1*	1.1	5.9*
House Maintenance	4.7	5.8	**6.0**	5.5	*4.0*	5.2	4.6	5.4	2.9*
Personal Maintenance	0.3	**0.4**	0.3	0.2	*0.1*	**0.4**	**0.4**	0.3	0.5
Social	*1.6*	**2.4**	1.8	2.3	2.3	2.2	1.8	2.0	1.3
Amusement	11.2	*8.6*	10.0	9.3	9.4	9.7	**11.9**	10.0	5.9*
Recreation	3.0	2.5	*1.9*	2.6	**3.2**	2.8	4.2	2.6	5.9*
Other	0.1	**0.4**	0.2	0.1	0.3	0.1	*0.0*	0.2	7.1*

* Statistically significant at the 0.05 significance level.

Note: **Bold** typeface indicates the **highest** mean for a particular activity type.
Italics typeface indicates the *lowest* mean for a particular activity type.

The findings are consistent with the information presented in Figure 5.9. As expected, the *Homebodies* group participates in amusement activities (dominated by in-home amusement) more than any other cluster.

5.3.1.2 Socio-demographic Characteristics of Travel Behaviour Clusters

The results of analysis of variance and chi-square tests on socio-demographic variables for the travel behaviour clusters are presented in Table 5.14. Rather distinctive characteristics emerge for some groups. For example, the *Transit / Walkers* cluster is found to have the largest proportion of females, smallest household size, and the greatest percentage of household heads. These attributes suggest that many members of this group are elderly women living alone. Furthermore, the group is the poorest with the largest percentage living in apartments. Finally, less than 44 percent have a driver's license and they have the smallest auto ownership of any group.

In contrast to the *Transit / Walkers* group, the *Adventurers* are predominately male, the youngest, most affluent, and have the most vehicles per household. The *Homebodies*, not surprisingly, are the oldest group, mostly female, have the fewest workers, have less than 68 percent who are licensed to drive, own the second fewest number of vehicles, and have the largest proportion who are disabled.

Overall, the remaining four clusters have similar socio-demographic characteristics although the *Auto Passengers* tend to be predominately female with fewer who are licensed to drive and a larger proportion who are disabled.

5.3.1.3 Stated-Adaptation Responses of Travel Behaviour Clusters

The stated-adaptation responses to the road pricing survey were analyzed for the seven clusters based on travel behaviour variables. The results are presented in Table 5.15. These results are similar to those of the other previous sections in that none of the stated-adaptation responses can be shown to vary significantly between the clusters due to the small sample size.

Overall, there is some variation in response preferences between the clusters. As shown, three of the clusters (*Frequent* and *Infrequent Local Drivers*, and *Walker / Driver*) all prefer to 'combine trips with others' as a means to cope with the road pricing strategies proposed. *Homebodies* preferred to 'make the

Table 5.14: Socio-demographic Variable Means for Travel Behaviour Clusters

Socio-demographic Variable	Travel Behaviour Cluster									
	Trnst./ Walker	Freq. Local Driver	Infreq. Local Driver	Walker /Driver	Advnt.	Auto Pass.	Home-Bodies	Entire Sample	F Stat.	χ^2 Stat.
Age	75.1	71.2	72.4	71.6	*70.2*	74.2	**76.7**	73.2	18.3*	
Gender (% male)	*30.3*	60.8	49.5	50.6	**63.4**	19.6	37.5	43.3		51.3*
Household Size	*1.65*	1.84	1.82	*1.65*	**2.07**	2.01	1.99	1.86	5.1*	
Relationship to Hshld. Head:										
% head	**73.0**	67.2	69.5	70.3	*46.3*	51.0	50.0	62.7		16.2*
% spouse	*12.4*	31.6	28.7	28.6	**48.8**	39.2	31.9	30.9		19.6*
% parent	7.9	*0.6*	1.3	1.1	2.4	8.3	**12.5**	4.5		45.6*
Home Type:										
% sngl. fam.dwell.	*52.8*	**84.2**	84.0	80.2	82.9	82.4	80.0	80.4		9.8
% apartment	**40.4**	10.5	*9.1*	14.3	12.2	11.3	16.2	13.7		57.0*
%trailer/mobile	*0.0*	1.8	3.8	2.2	**4.9**	**4.9**	2.5	3.1		8.8
Hshld. Income (x $1,000)	*25.4*	35.8	33.6	33.4	**38.4**	31.8	32.0	33.0	3.5*	
Employment:										
%full-time	3.4	7.0	**9.9**	3.3	4.9	1.5	*0.6*	5.5		28.7*
% part-time	5.5	9.4	7.6	6.6	**12.2**	2.9	*0.6*	6.0		10.8
% homemaker	*2.2*	3.5	3.6	3.3	**9.8**	5.4	4.4	4.1		4.8
% retired	85.4	79.5	77.9	85.7	*70.7*	86.8	**91.9**	82.6		4.2
Race:										
% Caucasian	*93.3*	96.5	96.7	97.8	**100.0**	96.6	96.2	96.5		0.1
% African-Amer.	**3.4**	1.2	0.2	1.1	*0.0*	1.5	*0.0*	0.9		7.8
% other	3.4	2.3	3.0	1.1	*0.0*	2.0	**3.8**	2.6		3.6
% with License	*43.8*	**100.0**	99.5	97.8	95.1	71.1	67.5	85.5		44.3*
% Handicapped	13.5	*2.9*	5.1	3.3	4.9	18.1	**25.6**	10.4		60.8*
No. of Vehicles	*0.69*	1.84	1.79	1.64	**2.10**	1.50	1.41	1.61	27.1*	
% ½-mile of LRT	6.7	**9.4**	8.6	8.8	*4.9*	6.4	6.9	7.8		2.2

* Statistically significant at the 0.05 level.

Note: **Bold** typeface indicates the **highest** mean for a particular adaptation response.
Italics typeface indicates the *lowest* mean for a particular adaptation response.

trip less often' while *Adventurers* and *Auto Passengers* chose none of the prescribed options (likely indicative of no adaptive response) most often. No responses were recorded for members of the *Transit / Walker* cluster.

Table 5.15: Non-Commute Stated-Adaptation Responses for Travel Behaviour Clusters

Stated-Adaptation Response	Travel Behaviour Cluster (average number of times chosen for the 8 scenarios)								
	Trnst./ Walker	Freq. Local Driver	Infreq. Local Driver	Walker/ Driver	Advnt.	Auto Pass.	Home-Bodies	Entire Sample	F Statistic*
make trip less often	---	4.0	3.4	2.4	*1.0*	3.0	**5.0**	3.4	0.4
combine trip with others	---	4.2	3.6	**5.3**	2.0	2.5	*0.0*	3.8	0.8
make trip at different time of day	---	**1.4**	1.0	0.9	*0.0*	*0.0*	*0.0*	1.0	0.2
look for a similar destination closer to home	---	1.6	2.4	**3.4**	1.0	2.0	*0.0*	2.2	0.5
do activity at home	---	0.8	0.4	**1.1**	*0.0*	*0.0*	*0.0*	0.5	0.4
not make trip at all	---	1.2	**1.5**	*0.0*	*0.0*	*0.0*	*0.0*	1.2	0.8
none of the above	---	*0.5*	1.1	0.4	**4.0**	**4.0**	3.0	1.0	2.3

* None are statistically significant at the 0.05 level.
Note: **Bold** typeface indicates the **highest** mean for a particular adaptation response.
Italics typeface indicates the *lowest* mean for a particular adaptation response.

5.4 Observations

Each of the three approaches used to segregate the elderly into more homogeneous subgroups has produced valuable insights into their varied lifestyles and travel characteristics. More important, linkages between travel needs, socio-demographic characteristics and travel behaviour have been established.

To facilitate the selection of the most appropriate cluster solution for inclusion in the simulation model, Table 5.16 was prepared to summarize the statistical comparisons made between the three final cluster solutions. As shown, the table summarizes the relative strengths of the F statistics developed through the ANOVA analyses, Bonferroni Multiple Comparisons that illustrate how many cluster means were significantly different from one another, and identification capabilities. These results are discussed below.

Table 5.16: Summary of Objective Cluster Comparisons

	Activity Engagement Clusters	Socio-demographic Clusters	Travel Behaviour Clusters
1. ANOVA Results	(overall strength of differences between clusters based on F statistics)		
Activity Variables	strongest	second	weakest
Socio-dem. Variables	weakest	strongest	second
Travel Activity Variables	strongest	second	weakest
Travel Behaviour	weakest	second	strongest
2. Bonferroni Multiple Comparisons	(% of matched pairs that are significantly different)		
Activity Variables	48.8%	26.7%	11.3%
Socio-dem. Variables	23.0	66.7	37.6
Travel Activity Variables	56.2	29.2	26.8
Travel Behaviour	24.0	52.7	59.5
3. Identifcation of Individuals	(percent of individuals correctly indentified based on socio-demographic variables)		
	29%	100%	38%

An issue that must be considered when selecting the most appropriate segregation taxonomy is the degree to which the clusters discriminate across each of the key activity, socio-demographic, and travel behaviour variables. As expected, each of the three cluster solutions was shown to provide the strongest differences (as measured with F statistics) across the same dimensions used for their delineation. For example, the travel behaviour clusters showed the strongest differences across the travel behaviour variables. Furthermore, each approach produced cluster sets which were found to have significant differences in many of the other variables not used for their cluster dimensions. Although the activity engagement clusters had the strongest differences across the activity engagement variables (with and without travel), they provided the weakest delineations between the socio-demographic and travel variables. In fact, key travel variables such as trip duration and mode share did not vary significantly between the clusters. The socio-demographic clusters generated the second strongest partitions in travel and activity engagement variables.

Although ANOVA tests the null hypothesis that the means are equivalent from cluster to cluster, it does not lend any insight into which pairs of means, or how many pairs, are significantly different. To explore these relationships further, a Multiple Comparisons of variable means was required. The Bonferonni technique was applied to the cluster means of all variables included in previous analyses. The Bonferroni technique is similar to doing multiple *t*-tests between all pairs of groups except that it adjusts the observed significance level based on the number of comparisons made (Norusis, 1993). This multiple comparison technique ensures that the number of pairs found to have significant differences is not overestimated. When many comparisons involving the same means are made, the probability that one comparison will turn out to be statistically significant increases. For example, if 5 means are grouped for pairwise comparisons, a total of 10 tests is made. When the null hypothesis is true, the probability that at least one of the 10 observed significance levels will be less than 5 percent is approximately 0.29. As the number of means being compared increases, so does the likelihood of finding one or more pairs to be statistically different even if the true means are equal.

To illustrate the meaning of the tabulated values, the following example is given. For the socio-demographic clusters there was a total of 150 matched pairs compared to examine the differences across the travel behaviour variables (i.e., comparing the means of six clusters results in 15 matched pairs which were applied to all 10 travel behaviour variables). The Bonferonni Multiple Comparisons analysis found that 79 of these 150 pairs (or 52.7 percent) were significantly different at a 5 percent level of significance.

The results of the Bonferroni analyses are comparable with those generated from the ANOVA F-tests. However, the percentages of matched pairs found to be significantly different through the Bonferroni comparisons provide additional insight into the strengths of the differences between the clusters developed by each of the three separate approaches. For example, the socio-demographic clusters are shown to have nearly as many significantly different matched pairs of travel behaviour variables as those developed by the travel behaviour clusters (i.e., 52.7 versus 59.5 percent).

As noted previously, a key to the successful incorporation of lifestyle segmentation into an activity-based model was that the individuals need to be identified, or classified, into the appropriate cluster using common or easily attainable data. The approach used in Chapter 6 relies on the ability to take an individual's key socio-demographic attributes to classify them into a cluster set with relatively unique travel needs and behaviours. Therefore, the ability to identify the individuals with the clusters delineated by each of the three approaches, using only their respective socio-demographic characteristics, was tested. If it could be shown, for example, that most respondents could be successfully classified into their appropriate travel behaviour clusters (based solely on their socio-demographic characteristics) then this would provide a feasible option for inclusion in the activity-based travel model.

To test the ability to identify individuals to cluster groups, the mean values of the socio-demographic variables for each of the three final cluster solutions were used to redefine the cluster centroids. Euclidean distances were then determined between each cluster centroid and individuals based solely on the respondent's socio-demographic attributes. Each individual was then assigned to the cluster that it was closest to in Euclidean space.

The clusters that were developed using activity engagement variables allowed the fewest individuals to be properly identified. Using the socio-demographic variables that deviate significantly between the clusters (refer to Table 5.4) as the basis for identification, only 29 percent of the 1150 respondents could be assigned to their correct activity engagement cluster. Similarly, only 38 percent of individuals could be correctly identified into the travel behaviour clusters based on their socio-demographic attributes. Finally, the socio-demographic clusters permitted all elderly respondents to be properly identified since cluster boundaries were, in fact, defined by the same variables as those being used for identification. From this perspective, clusters developed based on socio-demographic variables have a distinct advantage for inclusion in model development.

Although a lack of data for the stated-adaptation survey precluded many statistically significant findings, informal comparisons showed that preferred response patterns to the road pricing scenarios exist within each cluster. These results seem to support the premise that different lifestyle groups of the elderly will react to certain policies in consistently different ways.

A final criterion that had to be considered when choosing the clustering technique for inclusion in model development was the relationship of cluster dimensions to the planning policy options for the elderly. As previously noted, a segmentation base that defines user groups compatible with service options would be more useful than a base that does not.

Considering all of the prerequisites for cluster definitions, those delineated using socio-demographic variables provided the most appropriate framework to model the travel needs of the elderly. Given their ability to identify individuals, discriminatory capabilities, and ability to address policy issues specific to the elderly, the socio-demographic clusters were chosen as the basis for segmentation for further model development.

CHAPTER 6

ACTIVITY-BASED MODEL DEVELOPMENT USING MICROSIMULATION

This chapter presents the results of the efforts undertaken to develop three of the four modules of the activity-based travel model previously outlined in section 3.2. The three modules discussed include:

(1) Module 1: Categorization of Individuals.
(2) Module 2: Engaged Activity Patterns.
(3) Module 4: Assembly of Trip Tours

Since Module 3 (Adaptation Model introduced in section 3.2.3) takes different forms depending on the particular policy being studied it does not have a generic format that can be designed into the base simulation programming. Recall that the module is optional in the sense that it is only employed if the impacts of a proposed policy are being studied. As previously discussed, the application of the Adaptation Model could target the frequency distributions developed for Module 2 or the assembly of the activities into trip tours in Module 4. The implementation of the Adaptation Model is illustrated in Chapter 7 where exemplary test applications of the simulation model are undertaken.

Subsequent chapter sections describe the findings of analyses undertaken in support of the development of the remaining modules. The logic used for the programming of the simulation model to represent the framework is explained for each of the key steps within the modules. Many of the simulation steps relied on stochastic assignment of values which, in turn, were based on cumulative distribution functions derived from the Portland Metro activity-based survey. These distributions are presented and discussed in ensuing sections.

Some modules rely on constraining rules to temper model output. The analyses undertaken in support of these rules are discussed in subsequent sections. The outcome of verification tests to ensure the accuracy of the software programming and structure are summarized in the appropriate chapter sections. Finally, two levels of validation analysis are presented. First, Modules 2 and 4 are validated by comparing model output with the base data used to establish the imbedded distribution functions. Secondly, the model is applied to an external data set (Vancouver, WA survey) and the results contrasted against observed responses.

6.1 Module 1 Development: Categorization of Individuals

The first step in the modelling framework requires that each individual be classified into one of the six lifestyle clusters delineated in Chapter 5. This demands that each individual being included in the modelling effort has an array of socio-demographic attributes consistent with the cluster dimensions previously developed including age, gender, income, number of household vehicles, household size, driver's license, disability, household role, and employment status. Classification can be accomplished by undertaking the following three fundamental steps:

(1) Socio-demographic variables are *standardized* as discussed in section 5.2.

(2) Euclidean distances are calculated between the point defined by the individual's attributes and the centres of each of the six clusters (defined in Table 5.7).

(3) The individuals are assigned to the clusters to which they are closest (in Euclidean space).

It was originally proposed that a classification function be incorporated into the simulation model; however, the utilities available through most statistical software packages provide a more efficient means of manipulating the input data. By arranging the socio-demographic data for individuals being modelled in a matrix (with the rows representing each individual while the columns segregate the variables) the SPSS software package can assign each individual to the most appropriate cluster using its *CLASSIFY* utility. The only other required information is the cluster centres developed as a product of Chapter 5. The cluster centres have to be defined to enable the software to calculate Euclidean distances between each individual and the clusters. It is important to note that cluster centres remain fixed and are not recalculated each time an individual is classified.

The product gleaned from the classification analysis that is critical to the simulation program is the proportion of individuals who belong to each cluster. The proportions that were previously found for the Portland Metro data set were presented in Table 5.6. Survey data from any study area can be processed in the same way to segregate the elderly into the appropriate clusters. The proportions representative of each cluster are then coded into the simulation program for subsequent analyses. Individuals being simulated are then created in accordance with the observed lifestyle proportions.

The simulation program was designed to generate a single transaction (representing an elderly individual) and process it completely before the next transaction is created. Processing included the assignment of activities, application of constraints, and generation of trip tours. The model was designed so that the user defines the total number of elderly individuals to be simulated (i.e., representative of a specific study area) and the corresponding proportions that belong to each of the six predefined lifestyle clusters. With these dimensions provided, the model's first step following the generation of a transaction was to assign it stochastically to one of the six clusters using Monte Carlo simulation. The probability of assignment to each cluster was, of course, equated to the proportions who belong to each cluster. A complete listing of the programming code for the simulation is contained in Appendix C.

6.2 Module 2 Development: Engaged Activity Patterns

Once a transaction is created by the simulation model and assigned to one of the six lifestyle clusters it was then subjected to a series of processes encompassed by Module 2 which ultimately assigned a daily itinerary of specific activities. The activities were differentiated according to whether travel outside the home was required or not. The basic steps that the module followed are:

(1) Daily total number of activities were assigned based on cumulative distribution functions derived for each cluster.

(2) The number of activities that will require travel outside the home was defined as a function of the daily total number of activities.

(3) The specific activities were assigned to each of the eight classes previously defined in section 4.1. The probability of assignment to each of these activity classes was conditioned upon the daily total number of activities.

(4) Constraining rules tempered the minimum and maximum number of times a specific activity (e.g., meals, subsistence, personal maintenance, etc.) could be engaged in for a given day.

The analyses undertaken to develop the above empirical distributions and rule sets are described in the following sections.

6.2.1 Daily Number of Activities

The probability distributions for the daily total number of activities that individuals engage in were developed for each of the six lifestyle clusters. The results are depicted in Figure 6.1. Each cluster distribution is contrasted with the overall distribution which includes all of the elderly respondents. Interestingly, all clusters have a peak probability corresponding with six daily activities.

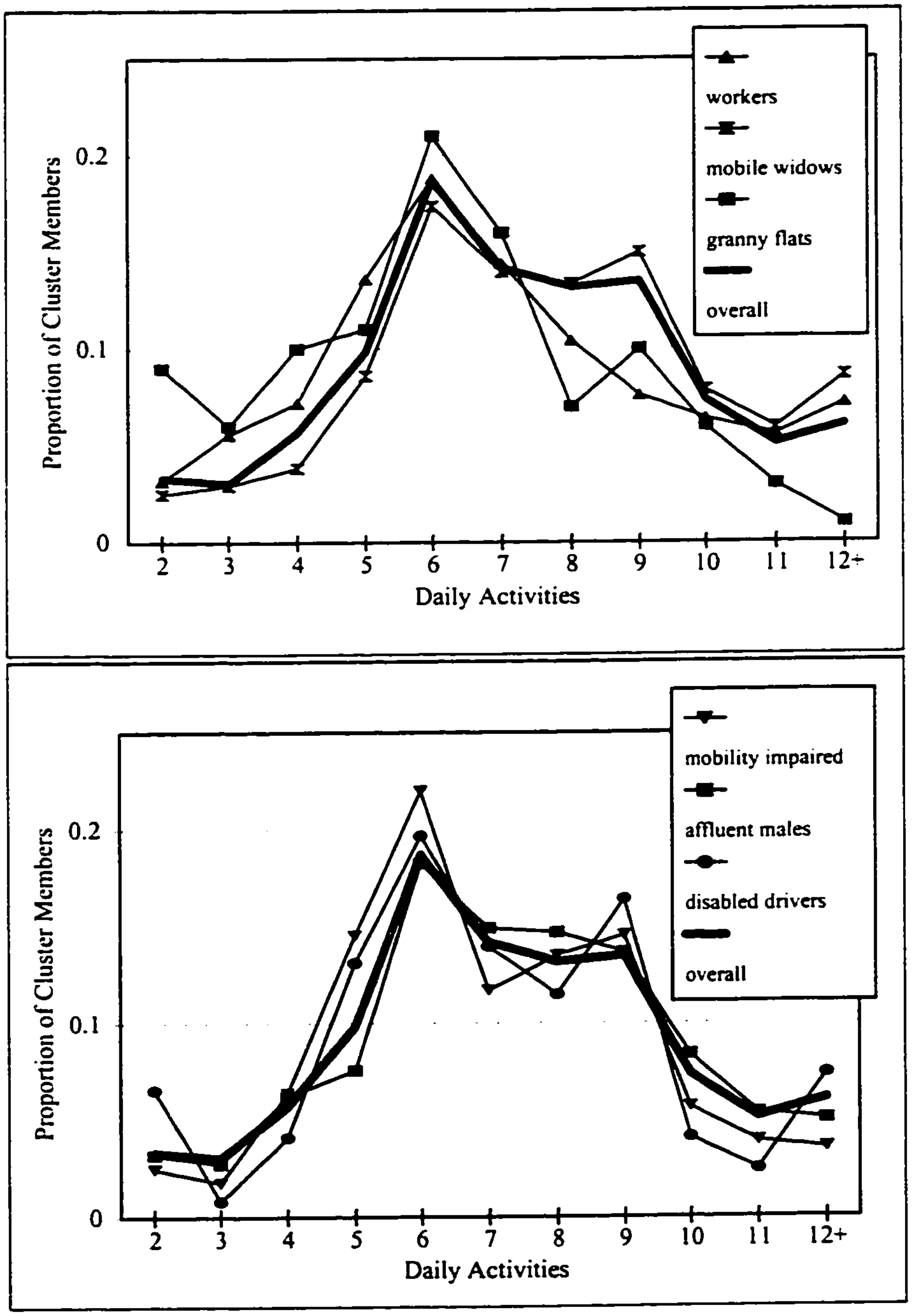

Figure 6.1: Daily Number of Activities

Standard chi-square tests were undertaken to detect if there were statistically significant differences in the cluster distributions compared with the overall distribution. The chi-square statistic was calculated as:

$$X^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \qquad [6.1]$$

where, X^2 = chi-square statistic.

O_i = observed frequency for the *i*th category.

E_i = expected frequency for the *i*th category.

k = the number of categories.

The categories in this context represented each number of daily activities (i.e., 2 through 12), while the observed frequencies were equated to the number of individuals associated with each category. The expected frequencies were developed based on the proportions of all of the elderly participating in specific numbers of activities per day. For example, it was found that 9.8% of all elderly respondents participate in exactly 5 activities per day. The expected number of elderly assigned to the *Workers* cluster who would participate in 5 activities per day was then calculated as 9.8% x 125 (number of people in cluster) = 12.

The null hypotheses were established to represent that there is no difference between the overall distribution of activities per day and each of the cluster distributions. Using a 5 percent level of significance, the null hypotheses were rejected for two of the clusters, namely the *Workers* and the *Granny Flats*. These findings suggest that, overall, there are no significant differences between the distribution of daily activities for four of the clusters and the elderly population as a whole. This allowed for the aggregation of the activity distributions for the four clusters for model development. The other two cluster distributions (*Workers* and *Granny Flats*) were considered unique and included separately using the empirical information. From Figure 6.1 it is seen that both of these distributions are skewed to the right indicating that greater proportions of the members engage in fewer activities per day relative to other clusters.

The probability distributions were subsequently transformed into cumulative probability distribution functions (PDF) and coded into the simulation model. The Monte Carlo simulation technique was then employed to assign stochastically a total number of daily activities to an individual using the appropriate PDF corresponding to their cluster membership.

6.2.2 Daily Number of Activities Requiring Travel

The first step undertaken to model the relationship between total daily activities and only those that require travel was to compare the distributions of travel frequencies between clusters. Figure 6.2 depicts the probability distributions of the number of daily activities that require travel for each of the six clusters. Each distribution was compared against an overall distribution that encompasses all of the elderly respondents. Interestingly, there is a large variation between the clusters in the proportion who do not participate in activities outside the home. For example, 57 percent of those belonging to the *Granny Flats* cluster had no activities that required travel for a given day compared to less than 10 percent of those in the *Workers* cluster.

Chi-square tests were undertaken in the same way as those outlined in section 6.2.1 to determine if cluster distributions were significantly different from the overall distribution. The results rejected the null hypothesis that there was no difference between these distributions for all but the *Mobile Widows* cluster. The *Mobile Widows* cluster is likely closely related to the overall distribution given that its members constitute nearly one-third of all of the elderly. These findings required that each cluster be assigned their travel requirements separately within the simulation model.

The number of travel activities to be assigned to an individual had to be conditioned on the total daily activities in which they would participate. For example, if one only participates in 2 or 3 activities in a day, they are much less likely to travel than those who engage in numerous activities. Probability distribution functions were developed for each cluster which described the proportion of cluster members who engage in an increasingly larger proportion of activities that require travel outside the home. Figure 6.3 depicts the probability distribution functions that were developed. As shown, each cluster has significantly different distributions. The y-intercept of the plots represent the proportion of cluster members not requiring travel for any activities outside the home. For example, 57 percent of the *Granny Flats* cluster members did not require travel for any of their daily activities.

With the probability distribution functions developed, the number of activities that require travel could be stochastically assigned to individuals using Monte Carlo simulation. To illustrate, suppose an individual had been classified to the *Workers* cluster and assigned 7 daily activities. Using a random number assigned to the individual between 0 and 1, the plot in Figure 6.3 can be entered on the y-axis and a corresponding percentage of activities requiring travel returned using the function. If the random number was 0.20, the corresponding percentage of activities requiring travel would be returned as 30.

The resulting number of travel activities would then be calculated as 30% x 7 = 2.1 (rounded to 2). This process was embedded into the simulation model.

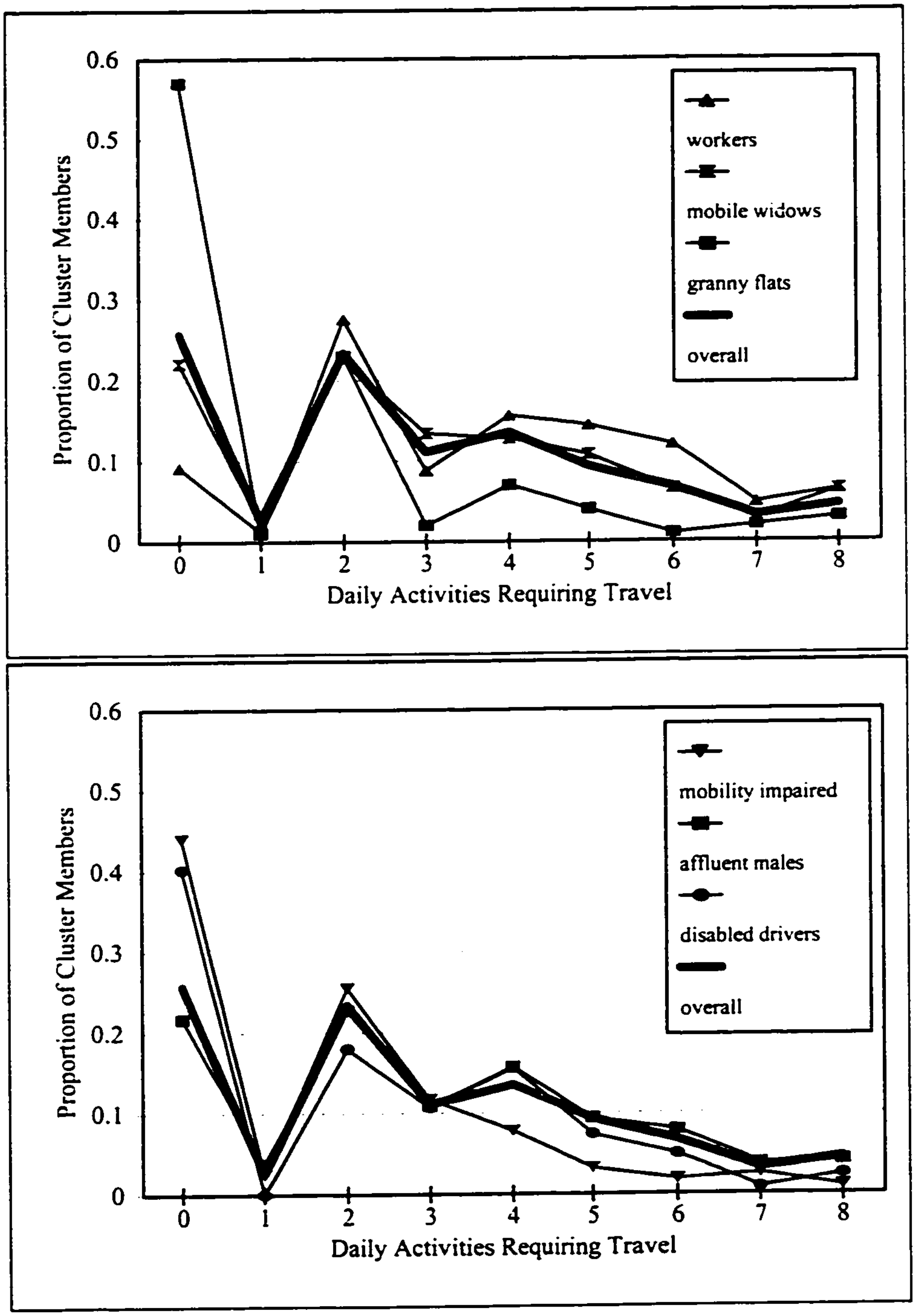

Figure 6.2: Daily Number of Activities Requiring Travel

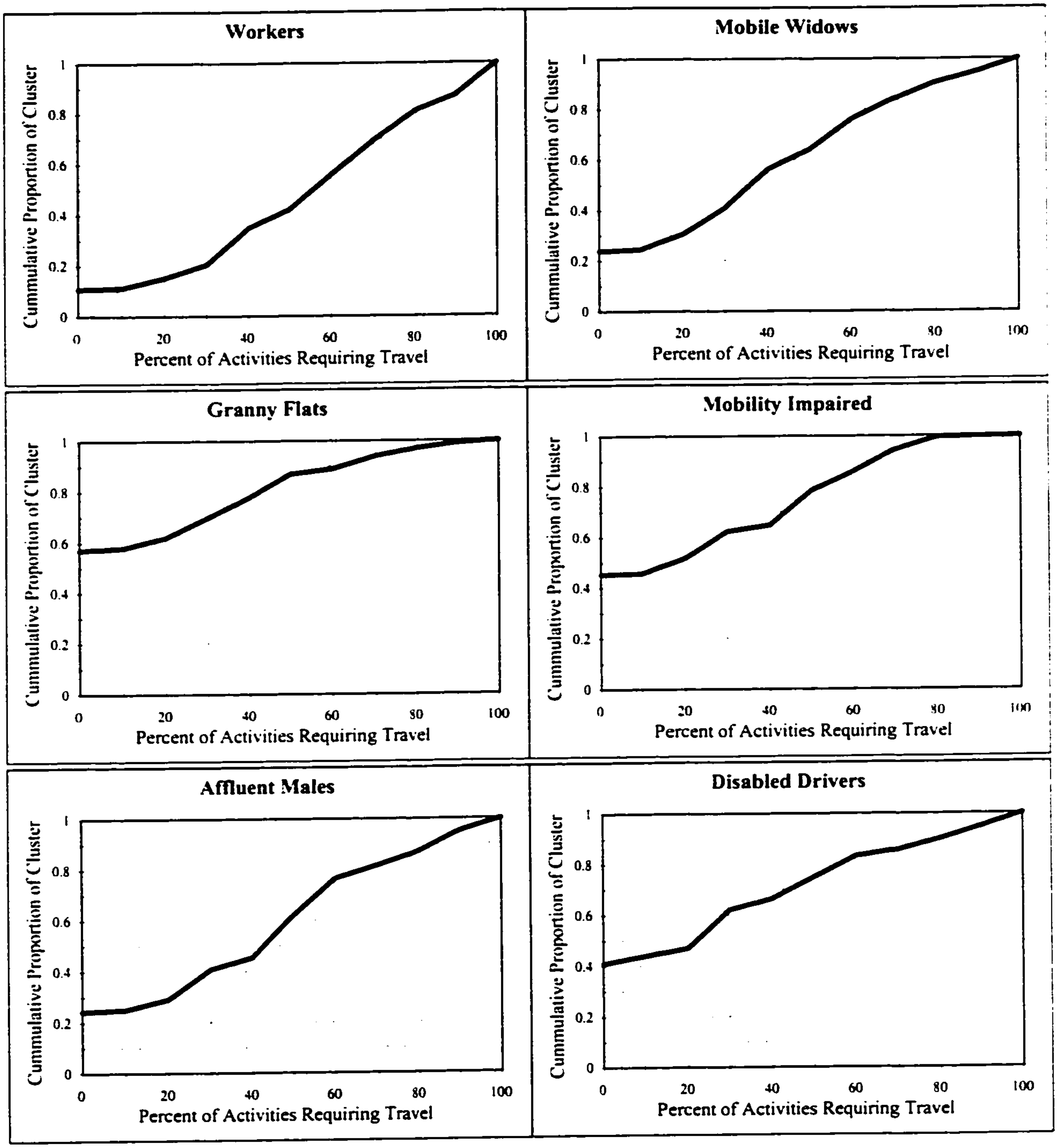

Figure 6.3: Probability Distribution Functions of Travel Activities

6.2.3 Assignment of Specific Activities

Once the total number of daily activities was assigned to an individual, each activity had to be assigned to one of the eight predefined classes (i.e., meals, subsistence, etc.). Rather than simply assigning these activities according to cluster-wide proportions, divisions were made to segregate the cluster members based on varying levels of daily activity. Segregations were informally drawn making sure that at least 30 individuals (to provide statistical significance) were included in each category. The premise was that those who are relatively inactive (or conversely overactive) will have varying propensities to engage in different classes of activities. For example, if only two daily activities are assigned to an individual belonging to the *Workers* cluster, the probability that one activity belongs to the subsistence class is relatively high. Conversely the probability that either activity is discretionary in nature such as social or recreation) will be relatively low. Again, these distribution functions were defined separately for each cluster.

Table 6.1 presents the results of the distributions developed for the *Workers* cluster. The table is shown to exemplify the distributions developed for each cluster (contained in Appendix D). The probability distributions were converted into cumulative distribution functions for use in the simulation program. The simulation model was written so that each daily activity was stochastically assigned to one of the eight classes using Monte Carlo simulation. The appropriate distribution function was utilized, conditioned on the total number of daily activities.

The data in Table 6.1 not only discriminates between the probability of engaging in different classes of activities but whether travel would be required for the specific activity or not. For example, if an individual is assigned 5 activities for a day, for each activity there is a 14.5 percent probability it will be a meal at home and an 11.5 percent probability it will be a meal taken away from home. Clearly, certain activities involve travel more often than others. The probability distribution functions were coded to differentiate when travel was required for a specific activity (e.g., the probability distribution function would return a value of '1' for a meal at home and '11' for a meal away from home).

A key step in the modelling process involved a continuity check between the expected number of travel activities (as determined through the steps described in section 6.2.2) and the number returned from the assignment of activity classes. If the two numbers did not agree, the transaction was returned to have the activity classes reassigned. This check ensured that the proportion of activities taking place outside the home accurately represented the empirical data.

Table 6.1: Distribution of Activities by Class for the *Workers* Cluster

Activity Classes		Activities per Day			
		0-4	5-6	7-8	9+
meals	without travel	12.0%	14.5%	16.9%	15.6%
	with travel	12.2	11.5	8.3	9.0
subsistence	without travel	2.3	1.5	7.0	3.4
	with travel	24.2	13.7	10.8	11.2
house maintenance	without travel	5.6	6.0	4.7	7.3
	with travel	9.8	12.2	11.6	14.1
personal maintenance	without travel	0.0	0.3	0.0	0.0
	with travel	0.0	0.5	1.1	1.6
social	without travel	0.0	1.0	1.5	1.7
	with travel	1.1	4.0	3.8	3.4
amusement	without travel	19.7	16.1	12.8	16.1
	with travel	8.8	8.7	9.3	4.2
recreation	without travel	2.1	6.0	3.8	2.3
	with travel	1.1	0.5	4.6	4.6
other	without travel	0.0	0.0	0.2	0.0
	with travel	1.1	3.5	3.6	5.5
	Total	100.0%	100.0%	100.0%	100.0%

Without this check, the model was found to underestimate the number of individuals who engaged in no activities that required travel. Similarly, the number of elderly who travelled to many activities was underestimated as well. In essence, a stochastic assignment of travel activities that relied solely on the distributions similar to those in Table 6.1 tended to homogenate the travel needs for individuals in each cluster. By using a stochastic assignment of activities, a binomial distribution for travel requirement became inherent in the process. In other words, the probabilities of engaging in specific numbers of activities away from home followed a binomial distribution because of the assignment process. The model's tendency to underestimate the number of individuals at either end of the spectrum suggests that the distribution of individual tendencies to travel to activities may not be properly represented by a completely stochastic process. Consequently, the tendencies for subgroups within each cluster to travel very little, or conversely quite often, may be diluted by a random assignment technique.

An additional explanation of the model's tendency to underestimate the number of individuals who engage in no or many activities away from home is related to the effect of averaging. Since the data were aggregated into three or four distributions (representing varying levels of daily activities) the proportions of activities which were assigned requiring travel were somewhat distorted due to averaging. For example, those allocated only 1 or 2 activities per day were assigned activities from the distribution representing 0 to 4 activities per day. The subsequent probabilities of engaging in the 1 or 2 activities away from home were consequently overestimated.

The continuity check that was developed accomplished two goals. It allowed the model to maintain the proper split between activities which are engaged within and away from home while still assigning a mix of activities consistent with empirical data. In retrospect, the same goal could have been accomplished by structuring the model to assign the activity types in two discrete steps. Once the numbers of activities taking place within and away from home were identified, the activity classes could have been assigned using distribution functions developed separately for those which require travel and those which do not.

6.2.4 Constraining Rules

Using the stochastic process previously described to assign activities can occasionally result in unreasonable itineraries. There is a chance (although small in most cases) that an abnormally high frequency of a particular activity could be assigned to an individual. For example, an individual participating in seven daily activities could, in fact, be assigned all seven as 'meals requiring travel'. Clearly, such an itinerary is unreasonable. Although the probability of assigning an individual this particular combination within the simulation process is very small (for *Workers* it would be $(0.083)^7$) a series of constraining rules was developed to guard against assigning too many, or too few, common activity types.

To help establish the constraining rules a set of probability distributions was developed for each activity class from the survey data. The probabilities associated with engaging in specific numbers of a particular activity were determined. Table 6.2 presents a summary of the cumulative probability distributions developed that encompassed <u>all</u> of the elderly. Similar distributions (presented in Appendix E) were developed for each specific cluster.

Table 6.2: Probability Distributions of Frequency of Activity Engagement by Activity Class (All Elderly Clusters)

Percent of Observations Less Than:	Activity Classes							
	meals	substn.	house maint.	persnl maint.	social	amsemnt	recreatn	other
1	8.1%	89.7%	25.7%	88.4%	65.1%	9.8%	55.9%	85.5%
2	30.3	96.0	52.1	98.6	88.6	37.4	87.9	95.3
3	68.8	98.7	75.0	99.8	97.3	66.8	96.9	98.3
4	96.3	99.3	87.7	100	99.3	85.9	99.5	99.5
5	99.1	99.8	95.1	100	99.9	94.9	100	100
6	100	100	98.0	100	100	98.1	100	100
7	100	100	99.3	100	100	99.7	100	100
8	100	100	99.7	100	100	99.8	100	100
9	100	100	100	100	100	100	100	100
Average Daily Participation	1.97	0.16	1.66	0.13	0.50	2.08	0.60	0.21

(N = 1,150 survey respondents x 2 days = 2,300)

The constraining rules were set so that maximum frequencies of engagement in each activity class would provide 99 percent coverage. For example, setting the maximum number of meals to 4 would give results that agree with 99.1 percent of the actual survey data. Similarly, establishing a maximum of 2 personal activities per day covered 99.8 percent of survey results. The 99th percentile threshold was set considering cluster sizes (ranging from 50 to 436) and a subjective review of the tabulated data. Cluster sizes were considered to determine the number of itineraries that could potentially be erroneously excluded. For example, using a 99th percentile on a cluster of 436 individuals would, on average, lead to a misrepresentation for 4 individuals. This level of error was considered reasonable given the study objectives. Future applications of the model and corresponding cluster sizes had to be considered as well. The tabulated data was reviewed to examine the implications of setting the threshold at different levels (e.g., 80th versus 90th versus 99th percentiles). In most cases, the threshold only changes marginally to provide much greater coverage. For example, raising the maximum allowable number of meals from 2 to 4 results in an increase in coverage from 68.8 percent to 99.1 percent.

Following a review of the distributions developed for each cluster, it was found that 99th percentile values were relatively consistent between clusters with one significant exception. The 99th percentile frequency of subsistence activities for the *Workers* cluster was found to be 5, while it was only 2 for all other clusters. The findings lead to the establishment of the constraining rules that are summarized in Table 6.3. As shown, none of the activities were limited to a minimum daily value for any activity class. All clusters were found to have at least 5 percent of their members who did not engage in a particular activity class during any survey day.

Table 6.3: Constraining Rules Used to Limit Assigned Activity Itineraries

Constraining Rules		Activity Classes							
		meals	subst.	house maint.	persnl maint.	social	amsemnt	recreatn	other
Minimum Daily Values	all clusters	0	0	0	0	0	0	0	0
Maximum Daily Values	*Workers* cluster	4	5	6	1	2	5	3	3
	all other clusters	5	2	7	2	3	6	4	3

The simulation model included the constraining rules by providing a final check of the assigned activity itineraries to ensure that the values in Table 6.3 were not exceeded. If the limits were surpassed, the individual was reassigned a completely new set of activities and tested again. Approximately 2 percent of individuals being processed were affected by these constraining rules.

6.2.5 Verification and Validation of Module 2

Several analyses were undertaken to ensure that the simulation model was properly synthesizing the assignment of activity itineraries for members of the elderly lifestyle clusters. The software verification examined the mechanics of the simulation programming while validation analyses ensured that the model outputs corresponded well with expected values. The software coding of the processes previously described was checked using the GPSS/H Debugger Utility. This facility allowed each transaction's progression to be tracked through each of the program steps. It can be considered a 'structured walk-through' of the model's programming. This permitted a review of the software coding to ensure that the simulation functions were, in fact, properly developed, coded and utilized.

The validation testing for Module 2 included a series of analyses comparing key dimensions of the model output with the survey data on which it was based. The distributions of the following variables produced by the model were summarized on a lifestyle cluster by cluster basis and compared against the base data set:

(1) Number of daily activities assigned to each person.
(2) Number of daily activities requiring travel assigned to each person.
(3) Number of daily activities by activity class.

Differences between model output and base data were inevitable for several reasons. First, the simulation relies on stochastic processes that introduce an element of randomness into the process. Much of the randomness can be controlled by running the simulation numerous times and averaging model outputs. Secondly, many of the probability distribution functions coded into the model necessarily aggregated the empirical data. For example, the probability distribution functions depicted in Figure 6.3 were cluster-wide aggregates of the survey data. Theoretically, separate distributions exist for every observed total number of daily activities. Furthermore, distributions similar to those presented in Table 6.1 necessarily aggregate values into ranges of activities per day rather than treating each level separately. Lack of sufficient numbers of observations and a necessity to simplify the simulation process results in the need for aggregation of data. Finally, the assumed linkages (between the items listed above) established by the framework may not be a completely representative synthesis or explanation of actual relationships thereby leading to discrepancies between model output and base data.

Table 6.4 summarizes the comparative analyses involving the assigned number of daily activities per person. The modelled values were determined by running the simulation program for a study group of 1,150 individuals (the equivalent size of the survey sample). In this context, the 'expected' values were determined based on the actual survey data. For example, it was known that 3.2 percent of the survey respondents belonging to the *Workers* cluster engaged in only two activities per day. If 125 *Workers* are simulated, then it was 'expected' that 4 (i.e., 0.032 x 125) individuals would be assigned to this cell in the matrix of Table 6.4. The actual model output, in this instance, was 5 individuals resulting in an overestimation for this cell.

Table 6.4: Total Daily Activities per Person -Model Output

Cluster		Daily Activities per Person											χ^2 calc.	χ^2 tabl.
		2	3	4	5	6	7	8	9	10	11	12+		
Workers	model	5	7	8	16	23	20	13	10	8	5	9	1.4	18.3
	expected	4	7	9	17	24	18	13	10	8	7	9		
Mobile Widows	model	4	11	12	26	56	52	44	55	25	20	32	3.6	18.3
	expected	9	10	13	29	59	47	45	51	27	20	29		
Granny Flats	model	4	3	4	4	11	9	4	6	3	2	0	1.2	12.6
	expected	5	3	5	6	11	8	4	5	3	2	1		
Mobility Impaired	model	3	2	10	21	30	15	20	21	7	6	6	0.7	15.5
	expected	4	3	9	21	31	17	19	21	8	6	5		
Affluent Males	model	15	14	27	33	81	64	64	54	36	22	27	2.3	18.3
	expected	14	12	27	33	80	65	64	60	37	24	22		
Disabled Drivers	model	4	0	2	4	11	9	9	12	3	1	5	2.8	12.6
	expected	4	1	3	8	12	9	7	10	3	2	5		
All Clusters	model	35	37	63	104	213	168	154	157	82	57	80	3.0	18.3
	expected	39	35	66	113	215	163	152	155	85	59	70		

note: a 5 percent level of significance was used for χ^2 tabulated. Degrees of freedom range from 6 to 10.

Chi-square tests were undertaken for each cluster to test the null hypothesis that there was no difference between the expected distribution of the number of daily activities per person and the observed (or model) distribution. The calculated chi-square statistics are presented in Table 6.4. At a 5 percent level of significance, none of the clusters produced a chi-square statistic that was significantly large enough to reject the null hypothesis indicative that the model output follows the expected distributions reasonably well. The overall fit of the model is expressed by combining all of the clusters into a single group and comparing the model output with the expected values for all of the elderly. The chi-square value of 3.0 is well below the threshold for rejection of the null hypothesis.

The tabulated values for chi-square in Table 6.4 are different for some clusters because it was necessary to combine some frequency categories of daily activities when the number of expected observations was small. For example, it was expected that only one member of the *Granny Flats* cluster would engage in

12 or more daily activities. It is generally accepted that categories should be combined such that the expected frequency (E_i) is at least five (Rosenkrantz, 1997). Subsequent chi-square analyses in this chapter list the tabulated chi-square values since categories were often combined to complete the goodness-of-fit tests properly.

Table 6.5 summarizes the comparative analyses involving the number of daily activities per person which required travel. Again, the expected values were derived from the actual survey data. The chi-square analyses tested the fit of the observed distributions (model output) against the expected distributions for each cluster. Using a 5 percent level of significance, the null hypothesis could not be rejected for any of the six clusters.

Table 6.5: Total Daily Travel Activities per Person -Model Output

Cluster		Daily Travel Activities per Person											χ^2 calc.	χ^2 tabl.
		0	1	2	3	4	5	6	7	8	9	10+		
Workers	model	12	3	27	16	23	13	13	8	3	1	5	8.0	14.1
	expected	12	2	35	11	20	18	15	6	3	2	3		
Mobile Widows	model	76	5	75	39	43	35	24	16	11	6	7	7.5	18.3
	expected	75	8	77	45	43	37	22	10	11	6	5		
Granny Flats	model	29	1	11	2	3	2	1	0	1	0	0	0.5	7.8
	expected	29	1	12	1	4	2	1	1	1	0	1		
Mobility Impaired	model	65	1	31	11	15	8	5	4	1	0	0	10.4	11.1
	expected	62	4	36	17	11	5	3	4	2	0	0		
Affluent Males	model	100	13	94	43	59	44	32	22	13	6	10	12.4	18.3
	expected	95	17	99	48	69	41	35	17	10	6	3		
Disabled Drivers	model	28	1	12	5	5	3	3	2	1	0	1	4.4	11.1
	expected	25	0	11	7	10	5	3	1	1	0	1		
All Clusters	model	309	26	257	116	149	106	78	49	29	14	17	9.2	19.7
	expected	296	30	269	128	155	107	78	37	26	14	13		

note: a 5 percent level of significance was used for χ^2 tabulated. Degrees of freedom range from 3 to 11.

The analyses summarized in Tables 6.4 and 6.5 simply showed that the model was accurately assigning daily totals of activities to individuals. The next step in model validation tested whether the model had assigned activities to specific activity classes in proportion to the distributions inherent in the survey data. The results of the comparative analyses for the number of daily activities by activity class are summarized in Table 6.6. These data include all activities, despite whether travel was required or not. As shown, the model estimates of activities by class are compared with the expected values and a chi-square statistic calculated. Again, the chi-square statistic was used to test the null hypothesis that the model predicted distributions were no different from what was expected as dictated by the survey data set. The calculated values of the chi-square statistic were significantly small enough that the null hypothesis could not be rejected for any of the clusters. Note that since the expected frequencies of subsistence activities was small for the *Granny Flats* and *Disabled Drivers* clusters, this activity class was combined with meals to calculate the chi-square statistic. The corresponding degrees of freedom were consequently reduced.

Table 6.6: Daily Activities by Class -Model Output

Cluster		Daily Activities (cluster totals)								χ^2 calc.	χ^2 tabl.
		meals	subsist	house maint	pers. maint	social	amsmnt	recrtn	other		
Workers	model	200	149	176	11	39	210	59	40	4.7	14.1
	expected	226	146	169	11	45	200	63	39		
Mobile Widows	model	699	20	696	59	216	718	197	84	3.6	14.1
	expected	705	17	677	52	206	729	187	88		
Granny Flats	model	91	3	53	5	10	99	28	9	1.0	12.6
	expected	89	3	50	5	8	94	28	11		
Mobility Impaired	model	285	8	153	12	65	294	88	10	1.0	14.1
	expected	276	7	156	14	66	291	92	10		
Affluent Males	model	834	17	802	66	222	906	272	96	2.8	14.1
	expected	847	15	774	61	224	937	276	94		
Disabled Drivers	model	131	0	104	6	23	142	41	7	1.9	12.6
	expected	125	1	97	9	26	134	39	8		
All Clusters	model	2240	197	1984	159	575	2369	686	245	2.8	14.1
	expected	2268	189	1924	152	575	2385	685	251		

note: a 5 percent level of significance was used for χ^2 tabulated. Degrees of freedom range from 6 to 7.

Table 6.7 summarizes the model output of only the daily activities that require travel, by class of activity. These data are analysed to ensure that the model generates the appropriate 'reasons' for travel among the members of the six clusters. None of the calculated chi-square statistics support rejection of the null hypotheses indicative that the model is synthesizing the base data properly.

Table 6.7: Daily Travel Activities by Class -Model Output

Cluster		Daily Activities (cluster totals)								χ^2 calc.	χ^2 tabl.
		meals	subsist	house maint	pers. maint	social	amsmnt	recrtn	other		
Workers	model	77	120	118	10	30	71	31	39	4.8	14.1
	expected	85	111	114	10	32	62	39	38		
Mobile Widows	model	190	14	378	53	125	168	114	82	4.2	14.1
	expected	189	12	359	47	120	159	102	87		
Granny Flats	model	9	1	20	4	5	6	7	9	1.6	12.6
	expected	12	2	20	4	5	8	7	11		
Mobility Impaired	model	44	4	77	10	28	47	23	10	3.2	14.1
	expected	37	4	74	11	25	40	23	9		
Affluent Males	model	244	11	460	63	138	229	151	96	4.7	14.1
	expected	233	9	426	59	134	222	149	92		
Disabled Drivers	model	25	0	50	6	13	19	6	6	1.1	12.6
	expected	28	1	50	9	14	21	8	8		
All Clusters	model	589	150	1103	146	338	541	332	241	6.9	14.1
	expected	583	138	1042	140	329	513	328	245		

note: a 5 percent level of significance was used for χ^2 tabulated. Degrees of freedom range from 6 to 7.

6.3 Module 4 Development: Assembly of Trip Tours

The model output from Module 2 produces an itinerary of specific activities requiring travel for each elderly individual being modelled. The next step was to assemble the activities into a set of trip tours so that a link could be made between travel needs and behaviour. Section 3.2.4 noted that a set of linear regression relationships was developed to predict the number of trip tours based on the characteristics of the activities that required travel. Recall that for this study, a trip tour is defined as the collection and sequencing of different activities, which require travel, into a linked journey that starts and ends at home. The incorporation of a series of activities into trip tours can be an extremely complicated process requiring a profusion of constraining conditions and optimization routines. As previously discussed, it was not the intent of this project to explore these relationships in depth; simple estimates of the number of trip tours were sufficient to permit a broader understanding of travel behaviour and policy effects.

Regression analyses were performed to develop a relationship between the total number of daily trip tours for an individual and independent variables which were the number of activities requiring travel by class (i.e., meals, subsistence, etc.). Initially, <u>all</u> clusters were included in a single model for the preliminary series of analyses to gain an overview of the relationships that exist. This provided a base model that was used for comparison against individual models developed for each of the six lifestyle clusters.

A *forward selection* technique was used to evaluate the suitability of each independent variable for inclusion in the model (Norusis, 1993). Variables were entered into the model one-by-one with those having the strongest correlations with the dependent variable included first. Student t tests were then constructed to determine whether the variable's coefficient was significantly different from zero or not. If the t statistic was not significantly large enough, the variable was excluded from the model. After each variable was added to the model, the coefficient of determination (R^2 value) was checked to ensure that its value was increased by including the incremental variable. Furthermore, variable bias was avoided by ensuring that the coefficients of the other variables did not change significantly following the inclusion of an additional independent variable. The resulting model that was developed for all of the elderly is summarized in Table 6.8. Note that the number of observations (N) is 2,300 which represents 1,150 survey respondents who provided two days of activity and travel information.

The R^2 value of the model presented in Table 6.8 is shown to be 0.802. This statistic represents the percent of variance in the number of tours per day explained by the independent variables included in the model.[1] In other terms, it is a statistic that tells how well the model fits the data and thereby represents a measure of the adequacy of the overall model. This finding compares favourably with the work of Goulias *et al* (1991) who developed a similar regression model for <u>all</u> age groups of a

1 Note that the mean number of daily trip tours for all of the elderly is 1.11 (see Figure 4.11) which has a variance of 0.90.

population. Their model yielded an overall $R^2 = 0.797$. They used independent activity variables classified as work, school, shop, social, and personal business.

Table 6.8: Trip Tour Model Including all Elderly Clusters

Independent Variable		model coefficient β	t statistic	level of signif. of t	Tolerance
TRAV_M	(meals)	0.395	18.2	0.0000	0.812
TRAV_SB	(subsistence)	0.221	8.3	0.0000	0.932
TRAV_H	(house maint.)	0.275	23.8	0.0000	0.887
TRAV_P	(personal maint.)	0.210	5.5	0.0000	0.937
TRAV_SC	(social)	0.305	13.2	0.0000	0.894
TRAV_AM	(amusement)	0.412	21.5	0.0000	0.921
TRAV_R	(recreation)	0.562	24.5	0.0000	0.969
TRAV_O	(other)	0.285	11.9	0.0000	0.854
Constant		0.259	7.1	0.0000	-

$R^2 = 0.802$ F = 577.4 Durbin-Watson = 1.73 Regression d.f. = 8 Residual d.f. = 1141
N = 2300

The values of the independent variable coefficients provide some interesting insights into travel behaviour. Theoretically, the largest value of these coefficients should be 1 since a single activity cannot, by definition, result in more than one trip tour. For example, holding all other variables constant, if an individual added one social activity to a daily itinerary, then the number of trip tours would not likely increase by more than 1. The corresponding coefficient listed in Table 6.8 can be interpreted to mean that for each additional social activity, there will be a corresponding increase of 0.305 trip tours. The larger the value of the coefficient, the lower the propensity for the individuals to link that activity with others in a trip tour. For example, the model coefficients indicate that recreational activities would be pursued more often than other types of activities in a trip tour with a single activity. Those variables with the smallest coefficients would, conversely, represent activities which tend to be linked to others in multiple stop trip tours. Interestingly, subsistence has one of the lowest coefficients which supposedly reflects the tendency to include other activities within the same trip tour from home (e.g., shopping after work, or travel to lunch during the work day). Goulias *et al* found a similar characteristic for work activities; however, they estimated a coefficient greater than 1 for social activities. Interestingly, they found that the coefficient for school activities was also close to a value of 1.

The *t* statistics presented in Table 6.8 indicate that the coefficients for all of the independent variables were significantly different from a value of 0. This indicates that each variable contributes to the explanation of the variance of the dependent variable about its mean.

The value of the Constant (or y-intercept) is shown to be 0.259. Theoretically this value should be 0 since no trip tours would be necessary if there are no activities which require travel. However, the constant term should neither be suppressed nor relied on for inference (Studenmund, 1992). Suppressing the constant term has the consequences of developing slope coefficients which are biased and *t* scores that are inflated. Furthermore, the intercept is generated in part by the omission of marginal independent variables, the mean effect of which is placed in the constant term. The true value of the intercept (without performing this task) may, in fact, be significantly different.

The *Tolerances* (TOL) presented in Table 6.8 are essentially measures of the severity of multicollinearity. It is determined as $1\text{-}R_j^2$, where R_j^2 is the value of the coefficient of determination obtained when the *j*th variable is regressed on the other independent variables (Norusis, 1993). The closer that the values of the tolerances are to 1, the weaker the correlation between the independent variables. Generally, as long as the tolerance values are greater than about 0.2, there is no reason to remove the variable from the model. Some authors and statistical software programs express the *Tolerance* with its reciprocal called the Variance Inflation Factor (VIF). Either approach provides one of the most comprehensive tests for multicollinearity available (Studenmund, 1992).

The F-statistic presented in the table tested the null hypothesis that all of the independent variable coefficients were equal to zero. Stated differently, it tests whether there is a relationship between the dependent variable and any of the independent variables. The F value of 577.4 provides a level of significance of 0.0000 associated with the rejection of the null hypothesis.

The Durbin-Watson statistic is a test for the presence of serial correlation of the residuals (Norusis, 1993). Possible values of the statistic range from 0 to 4. If the residuals are, in fact, not correlated with each other, the value of the statistic will be relatively close to 2. Values approaching 0 indicate stronger positive correlation, while those approaching 4 show negative correlation. The model presented in Table 6.8 has a Durbin-Watson statistic of 1.73 which demonstrates that no significant correlation exists among the residuals. If the results found that correlation did in fact exist, the causes could be attributed to an omitted independent variable or an incorrect functional form of the regression equation.

Figure 6.4 illustrates the model residuals by constructing a scatterplot of the observed values of trip tours against the model generated values. Since there are so many individual data points to be plotted, a *sunflower* diagram was used. Each sunflower groups all data points which would be plotted in a grid square and represents them as a single symbol. The symbol is a sunflower with varying numbers of petals. Each petal can be set to represent varying numbers of data points. In Figure 6.4 each petal represents 5 data points. Consequently, sunflowers with no petals represent 0 to 4 data points, 1 petal represents 5 to 9 data points, 2 petals represents 10 to 14 data points, and so on. Note that subsequent figures use varying scales for the petals.

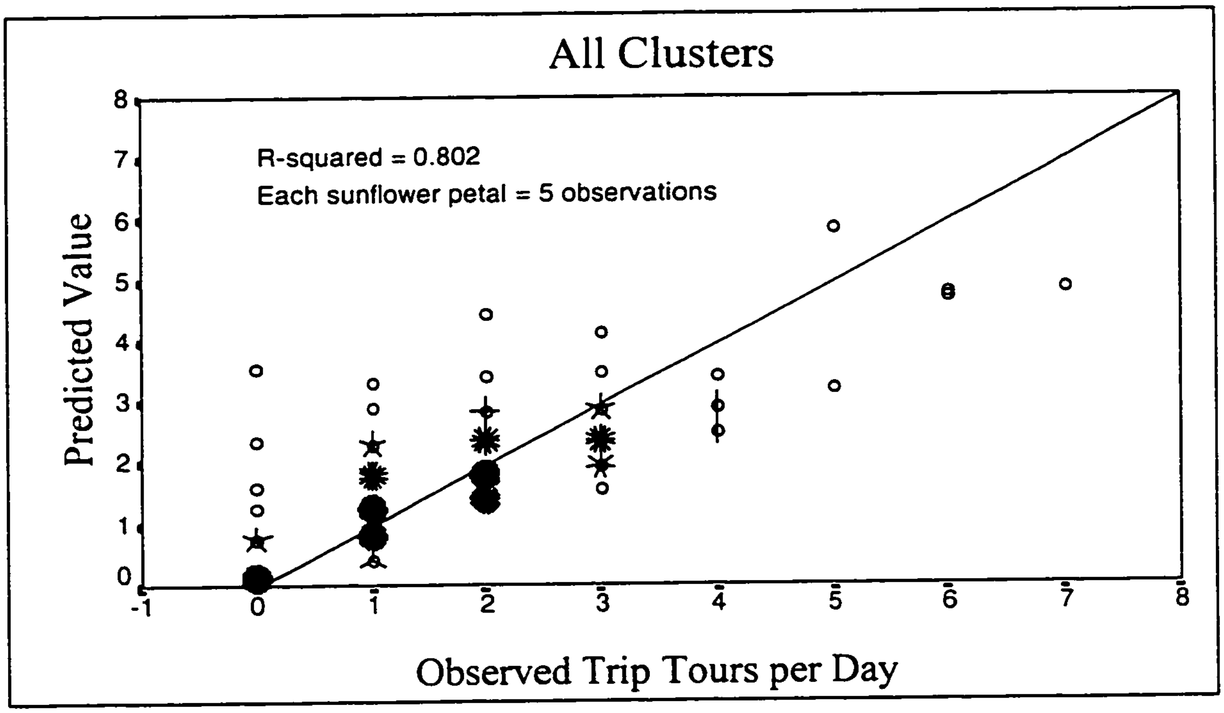

Figure 6.4: Regression Model for All Clusters -Residuals

The 45-degree diagonal line superimposed over the data in Figure 6.4 represents where all of the points would lie if a perfect fit existed between the observed values and model generated estimates. The closer the plotted points are to this line, the better the fit of the regression model. If any patterns in the distribution of residuals are shown by this type of plot then serial correlation should be suspected. As noted above, the Durbin-Watson statistic is typically used to test for the presence of serial correlation. It is seen that there is an overall tendency for the model to overestimate the number of trip tours for those who actually took one or no trip tours. Conversely, the model seems to underestimate the number of trip tours for those who were observed to have 3 or more tours. While these patterns suggest there may be some bias in the model, the Durbin-Watson statistic indicates that there is no significant serial correlation.

An issue illustrated by this plot is the fact that the regression model is being used to estimate a variable which is discrete in nature. The simulation model was programmed to round the results of the regression models to the nearest integer value. This additional step changes the residual values for each observation, thereby affecting the R^2 values. The net result that 'rounding off' the predicted number of trip tours on the R^2 statistic was determined for the above and subsequent regression models and found to change their values only minimally.

6.3.1 Cluster-Specific Regression Models

Once the regression model was developed for the elderly as an aggregated group, similar analyses were undertaken to develop cluster-specific models. These models provided the relationships which were included in the simulation model to estimate individual trip-making.

Table 6.9 summarizes the final version of the regression model developed for the *Workers* cluster. As shown, the R^2 value was found to be 0.649 and all coefficients for the independent variables were shown to contribute to the relationship. The variances of the model residuals are depicted in Figure 6.5. From the scatterplot it is seen that the shortcomings of the model are similar to those of the model for all clusters. It has a tendency to overestimate the number of trip tours for some of those who actually only had one. Conversely, it often underestimates the number of trip tours for those who actually had three or more. Recall that the scatterplot does not reflect that the simulation model rounds the predicted values to the nearest integer.

The model coefficients suggest that the elderly individuals belonging to the *Workers* cluster tend to link their subsistence activities with other activities more than the elderly do as a whole. Conversely, social activities tend to generate separate trip tours more often than the overall elderly population.

Table 6.9: Trip Tour Model -*Workers* Cluster

Independent Variable		model coefficient β	*t* statistic	level of signif. of *t*	Tolerance
TRAV_M	(meals)	0.457	7.8	0.0000	0.792
TRAV_SB	(subsistence)	0.110	2.6	0.0093	0.749
TRAV_H	(house maint.)	0.198	6.3	0.0000	0.906
TRAV_P	(personal maint.)	0.333	2.7	0.0077	0.931
TRAV_SC	(social)	0.483	6.1	0.0000	0.894
TRAV_AM	(amusement)	0.416	7.4	0.0000	0.972
TRAV_R	(recreation)	0.494	8.0	0.0000	0.943
TRAV_O	(other)	0.252	4.4	0.0000	0.839
Constant		0.283	3.9	0.0001	-

$R^2 = 0.649$ F = 55.7 Durbin-Watson = 1.79 Regression d.f. = 8 Residual d.f. = 241
N = 250

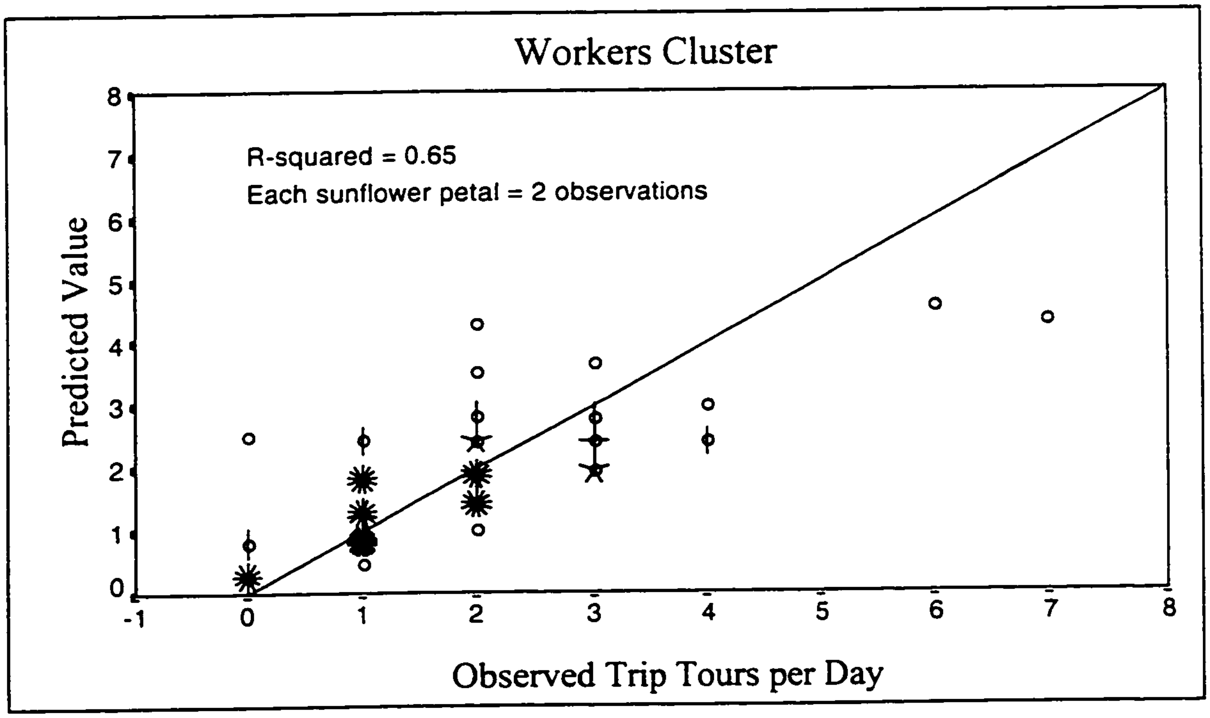

Figure 6.5: Regression Model for the *Workers* Cluster -Residuals

The final version of the regression model developed for the *Mobile Widows* cluster is summarized in Table 6.10. The R^2 value was 0.733 which is slightly less than that found for the model representing all of the elderly as a single group. The model coefficient for the independent variable representing the number of 'personal' activities was found not to be significantly different from 0 so it was excluded from the model. This can be interpreted to mean that the addition of a personal activity to an itinerary does not significantly influence the number of trip tours to be made (i.e., the activity will usually be included in an existing tour). The coefficient for subsistence activities was 0.438 compared with only 0.110 for the *Workers* cluster; suggesting that this elderly group is much more likely to make an additional trip tour when they participate in a work or school related activity away from home.

Figure 6.6 is a scatterplot representing the model residuals. As shown, the model often overestimates the number of trip tours required by those who actually only had one tour. Conversely, the model underestimated the daily total trip tours for a number of those who were observed to engage in two or three trip tours.

The dimensions of the regression model developed to predict the number of trip tours required by those belonging to the *Granny Flats* cluster is summarized in Table 6.11. An R^2 value of 0.932 resulted for this model which is a much stronger relationship than that achieved by the model developed for all clusters combined. The coefficients for all of the independent variables were found significantly different from 0. It is noteworthy that the coefficients for subsistence, social, and amusement activities are large compared with previous clusters. Again, the closer a coefficient is to 1, the stronger the propensity to undertake an additional trip tour when an incremental activity is included in a daily itinerary. The scatterplot of residuals depicted in Figure 6.7 illustrates the relatively good fit of the model to the data points.

The regression model developed for the *Mobility Impaired* cluster is summarized in Table 6.12 and depicted in Figure 6.8. The R^2 value developed by this model was 0.841 which is a better fit than the model representing the elderly population as a whole. Coefficients for all of the independent variables were found significantly different from 0. Compared with the elderly as a whole, this group is shown to be much less likely to make an additional trip tour to accommodate an incremental meal or 'other' activity. Consistent with all clusters, other than the *Workers*, the propensity to make an additional trip tour for an incremental subsistence activity is relatively high.

Table 6.10: Trip Tour Model -*Mobile Widows* Cluster

Independent Variable		model coefficient β	*t* statistic	level of signif. of *t*	Tolerance
TRAV_M	(meals)	0.369	13.0	0.0000	0.905
TRAV_SB	(subsistence)	0.438	4.9	0.0000	0.956
TRAV_H	(house maint.)	0.283	19.9	0.0000	0.939
TRAV_P	(personal maint.)	Variable not included in model *			
TRAV_SC	(social)	0.318	10.9	0.0000	0.931
TRAV_AM	(amusement)	0.369	14.7	0.0000	0.906
TRAV_R	(recreation)	0.495	15.3	0.0000	0.990
TRAV_O	(other)	0.228	7.3	0.0000	0.840
Constant		0.182	6.0	0.0000	-

$R^2 = 0.733$ F = 261.7 Durbin-Watson = 1.82 Regression d.f. = 7 Residual d.f. = 666 N = 674

* β coefficient was not statistically different from 0.

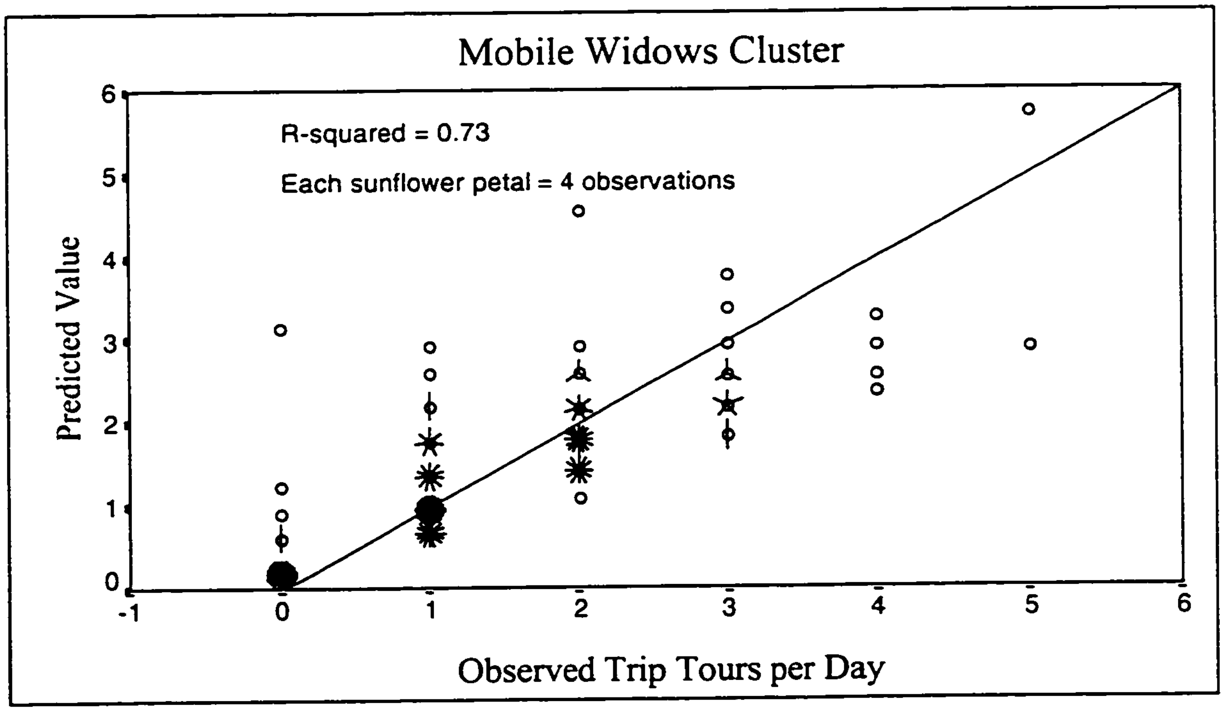

Figure 6.6: Regression Model for the *Mobile Widows* Cluster -Residuals

Table 6.11: Trip Tour Model -*Granny Flats* Cluster

Independent Variable		model coefficient β	*t* statistic	level of signif. of *t*	Tolerance
TRAV_M	(meals)	0.218	3.7	0.0003	0.631
TRAV_SB	(subsistence)	0.604	6.2	0.0000	0.877
TRAV_H	(house maint.)	0.299	10.5	0.0000	0.775
TRAV_P	(personal maint.)	0.273	3.6	0.0004	0.860
TRAV_SC	(social)	0.662	9.0	0.0000	0.927
TRAV_AM	(amusement)	0.562	9.1	0.0000	0.776
TRAV_R	(recreation)	0.271	4.4	0.0000	0.778
TRAV_O	(other)	0.396	12.5	0.0000	0.770
Constant		0.056	2.0	0.0452	-

$R^2 = 0.932$ F = 156.5 Durbin-Watson = 1.69 Regression d.f. = 8 Residual d.f. = 91
N = 100

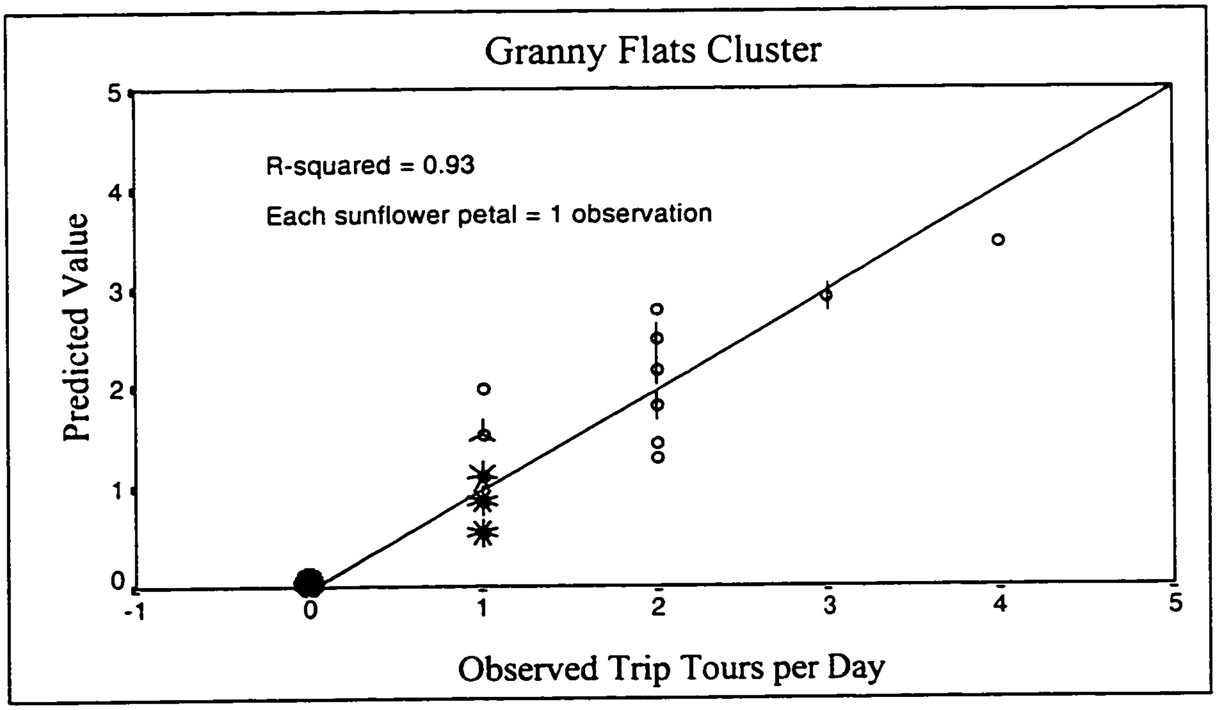

Figure 6.7: Regression Model for the *Granny Flats* Cluster -Residuals

Table 6.12: Trip Tour Model -*Mobility Impaired* Cluster

Independent Variable		model coefficient β	*t* statistic	level of signif. of *t*	Tolerance
TRAV_M	(meals)	0.277	7.4	0.0000	0.844
TRAV_SB	(subsistence)	0.492	4.8	0.0000	0.953
TRAV_H	(house maint.)	0.337	17.6	0.0000	0.874
TRAV_P	(personal maint.)	0.189	3.3	0.0012	0.924
TRAV_SC	(social)	0.379	9.5	0.0000	0.855
TRAV_AM	(amusement)	0.483	14.7	0.0000	0.862
TRAV_R	(recreation)	0.381	9.4	0.0000	0.927
TRAV_O	(other)	0.125	2.4	0.0153	0.893
Constant		0.076	3.2	0.0016	-

$R^2 = 0.841$ F = 180.0 Durbin-Watson = 1.98 Regression d.f. = 8 Residual d.f. = 273
N = 282

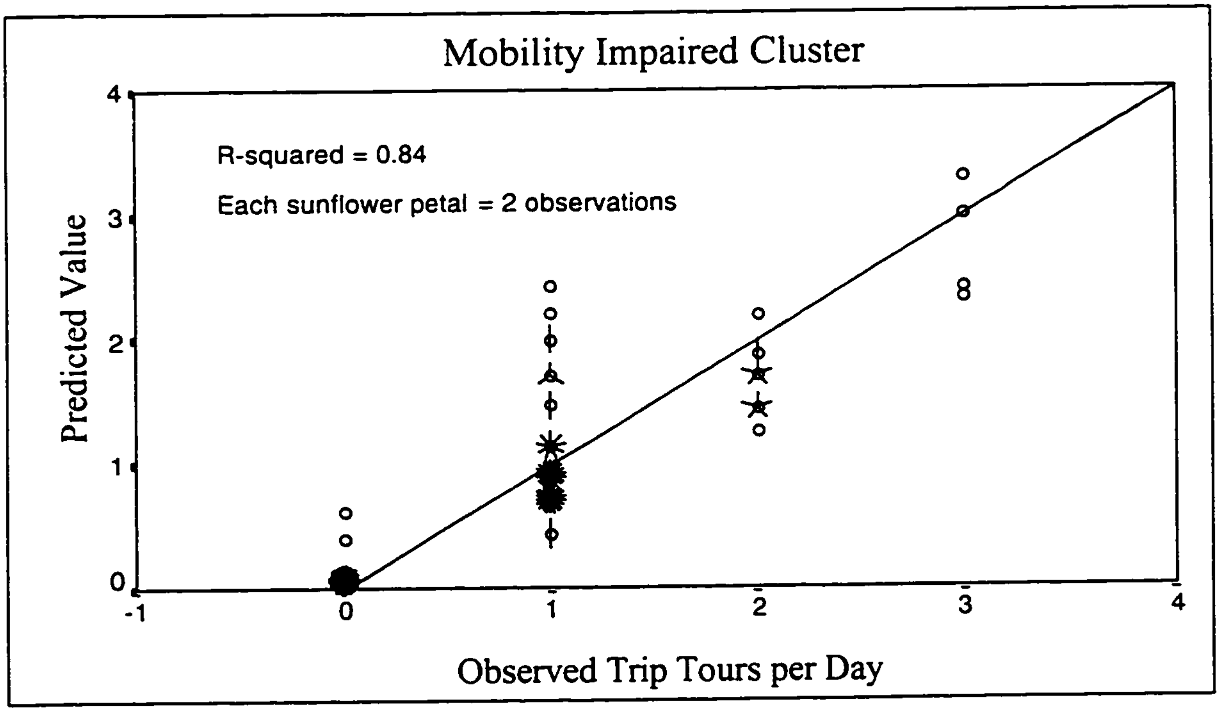

Figure 6.8: Regression Model for the *Mobility Impaired* Cluster -Residuals

The regression model developed for the *Affluent Males* cluster is summarized in Table 6.13. The R^2 value of 0.787 is only slightly below that found for the regression model developed for the elderly group as a whole. All independent variables were included in the model given that their coefficients were found statistically different from 0. It is noteworthy that the coefficient for the independent variable representing the number of recreational activities is significantly larger than all previous clusters.

Consistent with previous cluster models, the scatterplot depicted in Figure 6.9 illustrates that this model often overestimates the number of daily trip tours for those who actually had one. Similarly, the model often underestimates the number of trip tours for those who where observed to undertake three or more.

Table 6.13: Trip Tour Model -*Affluent Males* Cluster

Independent Variable		model coefficient β	*t* statistic	level of signif. of *t*	Tolerance
TRAV_M	(meals)	0.400	16.6	0.0000	0.891
TRAV_SB	(subsistence)	0.257	3.3	0.0012	0.996
TRAV_H	(house maint.)	0.287	22.3	0.0000	0.933
TRAV_P	(personal maint.)	0.226	5.9	0.0000	0.964
TRAV_SC	(social)	0.272	10.8	0.0000	0.938
TRAV_AM	(amusement)	0.429	20.7	0.0000	0.951
TRAV_R	(recreation)	0.591	22.7	0.0000	0.977
TRAV_O	(other)	0.355	13.0	0.0000	0.948
Constant		0.110	4.4	0.0000	-

$R^2 = 0.787$ F = 398.7 Durbin-Watson = 1.79 Regression d.f. = 8 Residual d.f. = 863
N = 872

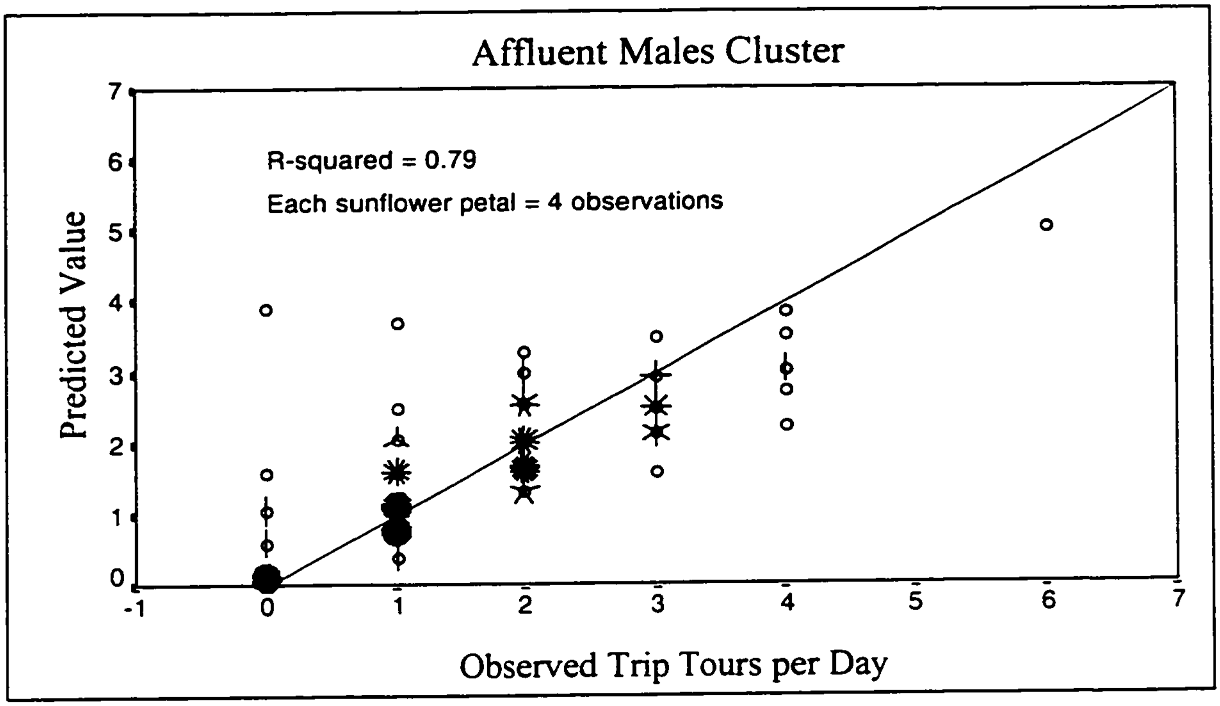

Figure 6.9: Regression Model for the *Affluent Males* Cluster -Residuals

Table 6.14 summarizes the regression model developed for the final cluster, the *Disabled Drivers*. An R^2 value of 0.817 indicates that this model fits the data it was developed on slightly better than the model developed for all of the elderly survey respondents. Note that two of the independent variables were excluded from the final version of the model given that their coefficients could not be shown to be statistically different from 0. Again, this can be interpreted to mean that most individuals in this cluster link these two activities with other activities in a trip tour rather than make an trip tour to service the activity. It is also important to recognize that the coefficient for recreational activities is 0.869 which suggests that most recreational activities tend to generate a separate trip tour. The value of the model's constant (or y-intercept) is only 0.074 which could not be shown to be significantly different from zero given the relatively high level of significance associated with this estimate.

The residuals of the model are depicted in Figure 6.10 which shows that the predicted values (once they are rounded to the nearest integer value) match the observed values relatively well.

Table 6.14: Trip Tour Model -*Disabled Drivers* Cluster

Independent Variable		model coefficient β	*t* statistic	level of signif. of *t*	Tolerance
TRAV_M	(meals)	0.487	8.5	0.0000	0.851
TRAV_SB	(subsistence)	Variable not included in model *			
TRAV_H	(house maint.)	0.230	8.5	0.0000	0.832
TRAV_P	(personal maint.)	Variable not included in model *			
TRAV_SC	(social)	0.174	2.8	0.0062	0.887
TRAV_AM	(amusement)	0.393	6.4	0.0000	0.844
TRAV_R	(recreation)	0.869	8.9	0.0000	0.978
TRAV_O	(other)	0.367	4.8	0.0000	0.921
Constant		0.074	1.6	0.1155	-

$R^2 = 0.817$ F = 85.7 Durbin-Watson = 2.16 Regression d.f. = 6 Residual d.f. = 115
N = 122

* β coefficient was not statistically different from 0.

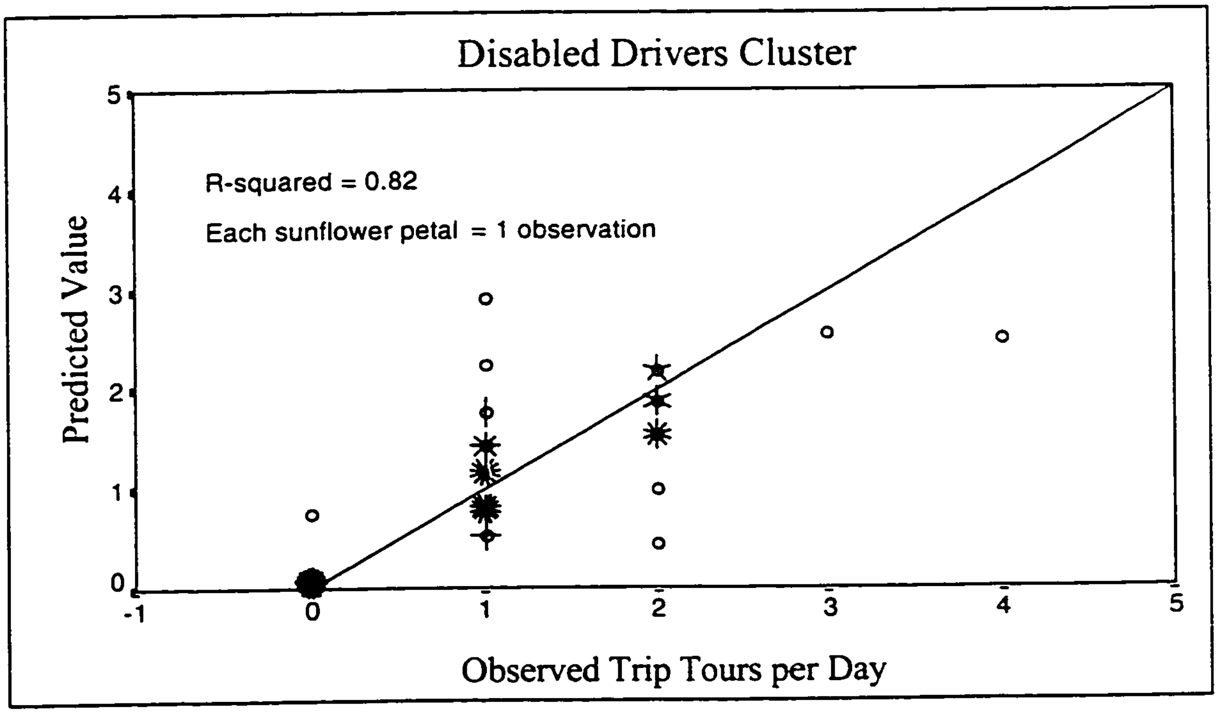

Figure 6.10: Regression Model for the *Disabled Drivers* Cluster -Residuals

6.3.2 Mode Split Function

Probability distribution functions were developed to assign stochastically the mode of travel for each of the trip tours generated by the regression functions discussed above. Figures 4.13 and 4.14 showed that the automobile is by far the most popular mode of travel among the different elderly age groups accounting for, on average, nearly 90 percent of all activities outside the home. Walking was found the next most common mode accounting for 10 to 20 percent of activities requiring travel. Furthermore, it was shown in Table 5.9 that when the elderly are grouped along socio-demographic dimensions, these mode split proportions vary significantly between clusters. For example, although the elderly as a whole walk for 9.4 percent of all trip tours, the corresponding value for the *Mobility Impaired* was found to be 24.4 percent. Given the significant differences in mode split proportions between the six clusters, it was decided that separate distributions would be developed for each cluster.

A series of exploratory analyses was undertaken to detect if significant differences in mode choice also existed between the different activity classes (i.e., do the elderly tend to use a particular mode more often for certain types of activities). Since the auto represents the dominant mode, only the significant complementary modes of walking and transit (bus and MAX) were examined in detail.

Before comparative values of mode usage could be established, it was necessary to compensate for the fact that there are differing participation rates in the activity classes for each cluster. For example, it was found that for the *Workers* cluster, 16.7 percent of their walking trips were made to subsistence activities while the average for all of the elderly is only 3.1 percent. This difference is expected given the disproportionate participation of the *Workers* in subsistence activities. Consequently, it was necessary to apply different weights to the values to account for varying propensities among the clusters to engage in different activity classes despite the travel mode chosen. Table 6.15 presents the results of this extension of the analyses. As shown, the values in the table represent the percent of activities which required travel that were reached by the walking mode, segregated by cluster and activity type. For example, it is shown that 4.8 percent of all meal-related activities requiring travel by *Workers* are accessed by walking.

Those activities accessed disproportionately more often by walking can be identified by comparing the tabled values with the weighted averages for each cluster. For example, the *Workers* walk, on average, to 5.5 percent of all activities that require travel. However, it is shown that they walked to nearly 24 percent of all recreational activities that took place away from the home. Considering the existence of some relatively small sample sizes, an informal conclusion from the data summarized in Table 6.15 is that the recreation activity class is the only category that experiences a significantly different access rate by walking among all of the clusters. A probable explanation of this observation is that the recreation class of activities includes the specific tasks of 'exercise and athletics' which includes the act of walking simply for the exercise. Considering these findings, it was decided to include separate distribution functions for the assignment of mode types to the trip tours. A modified distribution function was used to assign the mode of the first trip tour if a recreation activity was included in the itinerary of those requiring travel (developed by Module 2). The probabilities imbedded in these modified distribution functions were more heavily weighted to assign a trip tour to the walking mode than what the cluster-wide probabilities would dictate.

Table 6.15: Percent of Travel Activities Accessed by Walking

Activity Class	Cluster						All Clusters
	Workers	Mobile Widows	Granny Flats	Mobility Impaired	Affluent Males	Disabled Drivers	
meals	4.8%	8.8%	11.1%	20.5%	4.7%	5.0%	7.8%
subsistence	8.9	11.6	100.0	21.1	0.0	0.0	6.9
house maint.	2.9	7.4	13.2	31.9	4.2	5.5	8.0
personal maint.	4.0	2.1	0.0	19.3	2.3	0.0	4.0
social	3.9	10.7	25.2	12.3	6.9	4.9	9.1
amusement	3.3	7.2	23.0	22.2	6.2	4.9	8.3
recreation	23.8	21.1	18.5	28.6	22.1	17.1	24.3
other	5.4	8.1	6.0	18.4	2.5	0.0	6.0
weighted avg.*	5.5%	9.2%	16.0%	24.4%	6.7%	6.4%	9.4%
total observtns.	61	196	17	127	193	21	615

* weighted by number of observations in each activity class

The data presented in Table 6.16 represent the percentages of activities which require travel that were accessed by the transit mode. The statistical reliability of the data is severely restricted given the small number of observations for each cluster. The most notable observation is that the *Mobility Impaired* are shown to use transit at a rate of nearly twice their average when travelling to subsistence activities. However, because of the limited significance of the data, the distribution functions were not modified to reflect any differences that possibly exist between activity classes for any of the clusters.

Table 6.16: Percent of Travel Activities Accessed by Transit

Activity Class	Cluster						All Clusters
	Workers	Mobile Widows	Granny Flats	Mobility Impaired	Affluent Males	Disabled Drivers	
meals	0.9%	2.4%	0.0%	22.9%	2.5%	1.8%	4.2%
subsistence	2.0	0.0	0.0	32.9	7.6	0.0	3.2
house maint.	1.3	2.0	0.0	14.1	1.2	0.0	2.8
personal maint.	14.4	1.2	0.0	24.7	0.0	0.0	4.1
social	0.0	1.4	9.1	9.4	0.0	0.0	1.8
amusement	0.0	2.8	0.0	18.0	2.0	0.0	3.7
recreation	1.9	3.3	0.0	18.1	3.9	0.0	4.7
other	0.0	1.9	0.0	0.0	0.8	0.0	1.0
weighted avg.*	1.3%	2.2%	1.7%	16.5%	1.7%	0.6%	3.2%
total observtns.	9	42	1	81	31	2	211

* weighted by number of observations in each activity class

6.3.3 Verification and Validation of Module 4

The regression models that were developed for each lifestyle cluster to predict the number of trip tours for individuals were coded into the simulation program. Following the assignment of an activity itinerary (Module 2), the information concerning those activities requiring travel was used by the appropriate regression model to generate a corresponding number of trip tours that would be needed to service those activities.

The output from the regression model was modified within the simulation program in two ways before the final number of trips tours was assigned. First, the values developed by the models were rounded to the nearest integer since an individual can only participate in a discrete number of trips tours for any given day. Second, if the simulation program assigned at least one activity requiring travel, a continuity check was established to ensure that at least one trip tour was allocated. There were several instances where a single activity would be assigned that required travel, yet the regression model yielded a value for the number of trip tours which was rounded to zero. For example, if an individual belonging to the *Disabled Drivers* cluster was assigned one 'household maintenance' activity that required travel, the regression model would estimate the number of daily trip tours to be 0.304. This value would have been rounded to zero by the simulation model. Consequently, the individual would have then been assigned one activity away from home, yet engaged in no trip tours to service the need.

Software verification was undertaken to ensure that the logic of the programming was working properly. Again, the GPSS/H Debugger Utility was used to follow the steps that each transaction took as they progressed their way through the model.

The model output of the number of trip tours per day was compared against the survey data to validate that it could replicate the base information with a reasonable degree of accuracy. The analysis was undertaken on a cluster by cluster basis. Table 6.17 summarizes the results of the validation analysis. The data presented in the table represent the number of individuals generated by the model and those expected to have undertaken varying numbers of trip tours per day. Consistent with previous validation analyses, the model simulated 1,150 individuals in an effort to replicate the entire base data set.

Table 6.17: Total Daily Trip Tours per Person -Model Output

Cluster		Daily Trip Tours per Person						χ^2 calc.	χ^2 tabl.
		0	1	2	3	4	5+		
Workers	model	12	62	40	10	3	0	1.1	7.8
	expected	13	64	35	11	4	0		
Mobile Widows	model	79	153	86	25	4	0	1.5	9.5
	expected	83	154	82	22	6	0		
Granny Flats	model	27	15	4	1	0	0	0.0	6.0
	expected	27	15	4	1	0	0		
Mobility Impaired	model	59	48	20	3	0	0	5.4	6.0
	expected	59	56	12	3	0	0		
Affluent Males	model	101	169	121	38	10	0	5.9	9.5
	expected	107	185	104	36	7	0		
Disabled Drivers	model	28	23	7	2	1	0	4.3	6.0
	expected	25	23	11	1	1	0		
All Clusters	model	306	469	278	79	18	0	5.6	9.5
	expected	314	496	248	74	18	0		

note: a 5 percent level of significance was used for χ^2 tabulated. Degrees of freedom range from 2 to 4.

The null hypotheses that the model distributions were no different from the expected distributions (derived from the survey data) were tested with the chi-square statistic. The calculated values of the chi-square statistic were statistically small enough that the null hypothesis could not be rejected for any of the six clusters. Note that the number of degrees of freedom for the aggregated clusters ranged from 2 to 4 because some frequency categories of daily trip tours had to be combined where there were fewer than 5 observations expected. For example, the chi-square value for the *Granny Flats* cluster was based on combined categories of 0, 1, and 2 or more daily trip tours per person. Consequently, there were only two degrees of freedom for this cluster.

The fit of the regression models naturally had a direct impact on the model's ability to replicate the number of trip tours accurately. Their general tendency to underestimate the number of individuals who engage in only one trip tour daily is reflected in the model outputs in Table 6.17. Similarly, the regression models' general propensity to overestimate those engaging in two trip tours per day is also evident in the tabulated data. Nevertheless, a reasonably good fit has been achieved as demonstrated by the chi-square values. Overall, the model overestimated the total number of trip tours by only 3.7 percent (1,334 predicted versus only 1,286 observed).

Although very few activity-based models have reportedly been validated, the PCATS system provides a direct comparison of model accuracies. The PCATS model is based on a sequential decomposition of the probability associated with activity and travel patterns (Kitamura, 1997). The sequence adopted by PCATS is: activity type, location, travel mode, and activity duration. The model was analysed to determine how well it replicated observed activity and travel patterns. It was found that it underestimated the number of trips for the 374 sample individuals by 14.5 percent.

Note that the analyses summarized in Table 6.17 represent cluster totals and do not reflect a one-to-one correspondence with individual observations. For example, it is shown that the model overestimated the number of individuals from the *Mobility Impaired* cluster who would undertake 2 trip tours a day (20 estimated versus 12 expected). However, Figure 6.8 shows the regression model to underestimate the number of trip tours for those known to have taken exactly 2 in a day. The difference is explained by the inclusion of the number of individuals predicted to take 2 trip tours who, in fact, took 1 or 3 in a day.

Validation analyses were undertaken for the mode split function discussed in section 6.3.2. The data summarized in Table 6.18 represent the results of these analyses. Again, the simulation model was run to replicate the entire base data set of 1,150 elderly individuals. The numbers of trip tours generated by the model are segregated by mode type and cluster. These values are contrasted against expected numbers of trip tours reflecting the survey information. For example, it was expected that two transit trip tours would be made by the *Workers* cluster members. This value was determined by multiplying 1.3 percent, which is the transit mode share found from the survey (Table 5.9), by the total number of trip tours (=184) being modelled for this cluster.

The null hypotheses that the distributions of the model generated estimates were no different that the expected distributions were tested using the chi-square test. Since none of the calculated chi-square values were greater than the tabulated value, the null hypothesis could not be rejected for any of the clusters.

Table 6.18: Mode Split -Model Output

Cluster		Trip Tours by Mode					χ^2 calc.	χ^2 tabl.
		auto (personal)	auto (non-personal)	walk	transit	other		
Workers	model	163	6	13	2	0	1.5	7.8
	expected	167	4	11	2	0		
Mobile Widows	model	329	24	47	11	5	2.7	9.5
	expected	339	25	39	9	4		
Granny Flats	model	20	1	4	0	1	1.1	6.0
	expected	19	1	4	1	1		
Mobility Impaired	model	29	27	21	17	3	0.8	9.5
	expected	30	24	24	16	3		
Affluent Males	model	486	14	50	10	5	4.1	9.5
	expected	498	14	38	10	5		
Disabled Drivers	model	42	1	3	0	1	1.5	7.8
	expected	40	3	3	0	1		
All Clusters	model	1069	73	138	40	15	3.8	9.5
	expected	1093	71	119	38	14		

note: a 5 percent level of significance was used for χ^2 tabulated. Degrees of freedom range from 2 to 4.

6.4 Application of Model to an External Data Set

With the acquisition of the preliminary results of an external survey, it was possible to extend the validation analyses to a data set other than the Portland Metro survey which provided the basis for the development of the simulation model. The preliminary data sets associated with a complementary activity-based survey carried out in Vancouver, Washington (refer to Table 3.1) were available for use as a test case to validate the modelling framework. The Vancouver data contained essentially the same activity-based, socio-demographic, and travel variables as those recorded in the Portland Metro study. In total, 404 elderly respondents were interviewed through this survey. Using only the socio-demographic information associated with these respondents, the simulation model was applied. The model outputs were then compared, on a cluster by cluster basis, to the corresponding activity and travel behaviour information recorded in the survey database.

The first step in modelling the elderly respondents covered by the Vancouver survey was to classify each of them into one of the six predefined lifestyle clusters. The socio-demographic variables used to define the cluster dimensions were standardized (consistent with the procedures outlined in section 5.2) before the SPSS *CLASSIFY* utility could be applied. After each individual was assigned to one of the clusters, the information was summarized and is presented in Table 6.19. The distribution of the Vancouver respondents among the six lifestyle clusters is remarkably close to those included in the Portland Metro survey. Given the smaller number of elderly individuals covered by this data set, it is seen that the membership sizes for some clusters are unavoidably small (e.g., only 16 in the *Disabled Drivers* cluster). The scarcity of observations in some clusters had an influence on the statistical significance of some of the comparative analyses that follow.

The distribution function in the simulation model that assigned transactions their cluster membership was changed to reflect the percentages identified in Table 6.19. Following this change, the model was run to generate the output variables for an equivalent number of individuals as contained in the Vancouver data set (i.e., 404). Once the model outputs were obtained, validation analyses similar to those presented in previous sections were undertaken to compare the model predictions with the actual survey responses among the Vancouver respondents.

Table 6.20 contrasts the total number of daily activities the model assigned to each individual with those observed through the Vancouver survey. Again, the chi-square statistics are used to test the null hypotheses that there is no difference between the expected and model-generated distributions of daily

Table 6.19: Cluster Membership of Vancouver Survey Respondents

Cluster	Number of Members	Percent (Vancouver, WA.)	Percent (Portland Metro)
Workers	40	9.9%	10.9%
Mobile Widows	113	28.0	29.3
Granny Flats	21	5.2	4.3
Mobility Impaired	52	12.9	12.2
Affluent Males	162	40.0	37.9
Disabled Drivers	16	4.0	5.3
Total	404	100.0%	100.0%

Table 6.20: Total Daily Activities per Person -Model Output for Vancouver, WA

Cluster		Daily Activities per Person											χ^2 calc.	χ^2 tabl.
		2	3	4	5	6	7	8	9	10	11	12+		
Workers	model	2	3	3	6	7	6	5	3	2	3	4	2.9	12.6
	expected	2	2	3	7	7	5	6	5	2	2	2		
Mobile Widows	model	1	5	5	9	21	15	15	16	8	6	11	4.0	15.5
	expected	1	4	4	11	18	19	14	15	12	6	9		
Granny Flats	model	1	1	2	1	4	3	1	3	1	0	0	4.5	6.0
	expected	0	1	0	1	3	4	2	3	2	1	0		
Mobility Impaired	model	1	1	4	8	11	4	8	8	2	1	2	1.7	12.6
	expected	3	1	2	6	10	6	9	8	3	1	2		
Affluent Males	model	6	5	12	11	32	23	25	22	15	9	8	7.5	18.3
	expected	5	6	8	12	27	24	31	22	11	8	12		
Disabled Drivers	model	1	0	0	1	3	3	1	3	1	1	1	1.7	6.0
	expected	0	0	1	2	3	3	1	2	1	0	1		
All Clusters	model	12	15	26	36	77	54	55	54	29	20	26	7.3	18.3
	expected	11	14	18	39	68	61	63	55	31	18	26		

note: a 5 percent level of significance was used for χ^2 tabulated. Degrees of freedom range from 2 to 10.

travel activities. The calculated chi-square values suggest that the model fit is reasonably good. In fact, the chi-square values are only slightly higher than those in Table 6.4 which compared the model outputs with the base data set. Note, however, that the number of individuals included in each cluster of Table 6.20 is smaller than those from Table 6.4.

The number of daily activities developed by the model which require travel are compared in Table 6.21 with the observed values gleaned from the Vancouver survey. Comparing the calculated chi-square statistics with the critical tabulated value, it can be inferred that the model fits the Vancouver data reasonably well. Interestingly, it is shown that the model underestimated the number of individuals who would engage in 1 to 4 travel activities per day. Conversely, the model overestimated the number of elderly who would travel to participate in 5 to 9 activities per day. This overall pattern, however, is consistent with the results obtained for the base model (presented in Table 6.5).

Table 6.21: Total Daily Travel Activities per Person -Model Output for Vancouver, WA

Cluster		Daily Travel Activities per Person											χ^2 calc.	χ^2 tabl.
		0	1	2	3	4	5	6	7	8	9	10+		
Workers	model	4	1	10	6	8	5	4	2	1	0	1	2.4	9.5
	expected	2	1	9	7	9	4	4	4	2	1	0		
Mobile Widows	model	23	1	27	14	14	12	9	6	2	1	3	11.0	12.6
	expected	19	3	32	16	19	12	7	3	1	0	1		
Granny Flats	model	9	1	3	1	1	1	0	0	0	0	0	1.6	6.0
	expected	6	2	4	1	1	0	1	0	1	1	0		
Mobility Impaired	model	23	0	13	4	6	2	1	1	0	0	0	3.6	6.0
	expected	26	1	15	5	4	0	0	0	0	0	0		
Affluent Males	model	39	5	34	16	22	19	12	9	4	2	4	15.1	15.5
	expected	36	5	40	27	21	11	10	5	4	4	3		
Disabled Drivers	model	5	0	3	2	1	1	1	0	0	0	0	0.25	6.0
	expected	4	1	4	2	1	1	1	0	0	0	0		
All Clusters	model	103	8	93	44	53	40	27	18	7	3	8	15.3	16.9
	expected	93	13	104	58	55	28	23	12	8	6	4		

note: a 5 percent level of significance was used for χ^2 tabulated. Degrees of freedom range from 2 to 9.

Table 6.22 contrasts the distributions of activities by class (i.e., meals, subsistence, etc.) developed by the simulation model against those observed in the Vancouver survey data. The relatively high values of the chi-square statistics suggested rejection of the null hypothesis for two of the six lifestyle clusters, namely the *Workers*, and the *Affluent Males*. Although the chi-square values for these clusters are statistically significant, an informal review of the data shows that the values generated by the model match the expected results quite well within most of the activity classes. It is, however, noted that the model tends to overestimate the number of subsistence activities for all clusters.

Table 6.22: Daily Activities by Class -Model Output for Vancouver, WA

Cluster		Daily Activities (cluster totals)								χ^2 calc.	χ^2 tabl.
		meals	subsist	house maint	pers. maint	social	amsmnt	recrtn	other		
Workers	model	67	53	57	3	14	70	21	16	16.1	14.1
	expected	69	41	64	4	23	63	13	11		
Mobile Widows	model	234	7	227	19	67	219	66	28	4.1	12.6
	expected	238	1	209	18	71	242	66	26		
Granny Flats	model	36	1	19	2	4	38	9	3	7.2	11.1
	expected	36	0	23	2	11	40	7	6		
Mobility Impaired	model	109	3	60	4	24	119	33	3	6.6	11.1
	expected	122	2	56	10	24	123	42	2		
Affluent Males	model	305	8	307	26	83	347	102	36	14.6	14.1
	expected	345	3	298	26	84	345	109	42		
Disabled Drivers	model	29	0	27	0	8	30	8	3	2.0	9.5
	expected	31	0	19	3	6	29	10	1		
All Clusters	model	780	72	697	54	200	823	239	89	22.5	14.1
	expected	841	47	669	63	219	842	247	88		

note: a 5 percent level of significance was used for χ^2 tabulated. Degrees of freedom range from 4 to 7.

Most of the difference in the distributions often comes from one or two specific classes of activities. For example, the total number of subsistence activities predicted for the *Affluent Males* cluster was 8 compared with only 3 observed in the survey data. This one comparison represents 8.3 of the value of

14.6 calculated for the chi-square statistic. These anomalous data pairs may be due, in part, to the small number of individuals being analyzed for each cluster.

Given the small number of expected values for subsistence activities among all clusters except the *Workers*, these activity classes were combined with the meals category for the calculation of the chi-square statistic. Similarly, the personal maintenance activities were combined with household maintenance activities for the *Granny Flats* and *Disabled Drivers*. Finally, the other activities were combined with recreational activities for the *Mobility Impaired* and *Disabled Drivers* clusters.

Similar findings were observed when the travel activities by class were contrasted in Table 6.23. Two of the six lifestyle clusters developed chi-square statistics greater that the tabulated value corresponding with the 5 percent level of significance. Again, a few isolated pairs of data points contribute heavily to

Table 6.23: Daily Travel Activities by Class -Model Output for Vancouver, WA

Cluster		Daily Activities (cluster totals)								χ^2 calc.	χ^2 tabl.
		meals	subsist	house maint.	pers. maint.	social	amsmnt	recrtn	other		
Workers	model	25	43	38	3	10	25	10	16	7.7	14.1
	expected	25	37	45	4	16	21	9	11		
Mobile Widows	model	69	5	126	18	39	53	39	27	13.6	12.6
	expected	57	1	104	17	44	46	30	25		
Granny Flats	model	4	1	6	2	2	3	3	3	8.0	9.5
	expected	6	0	15	2	5	5	2	6		
Mobility Impaired	model	17	2	30	3	11	19	7	3	40.6	11.1
	expected	11	1	19	7	5	7	9	2		
Affluent Males	model	94	6	178	22	51	94	56	36	7.6	12.6
	expected	79	1	168	25	56	88	53	41		
Disabled Drivers	model	4	0	15	0	5	4	1	3	5.9	6.0
	expected	4	0	8	3	2	3	1	1		
All Clusters	model	213	57	393	48	118	198	116	88	24.3	14.1
	expected	182	40	359	58	128	170	104	86		

note: a 5 percent level of significance was used for χ^2 tabulated. Degrees of freedom range from 2 to 7.

the high chi-square values. For example, the difference in amusement activities for the *Mobility Impaired* cluster (i.e., 19 predicted versus 7 expected) accounts for 20.6 of the 40.6 chi-square value. Informal comparisons suggest the model fits the survey data reasonably well with a few exceptions. Activity classes were again combined to ensure an adequate number of expected observations in the same manner as for the analyses summarized in Table 6.22. A notable exception is for the *Disabled Drivers* where all discretionary activities were grouped together to permit the calculation of a chi-square value.

Perhaps the most basic, yet important validation test of the simulation model is represented by the data contained in Table 6.24. The number of daily trip tours estimated by the model for each individual is compared with the number recorded in the survey data set. The model overestimated the total number

Table 6.24: Total Daily Trip Tours per Person -Model Output for Vancouver, WA

Cluster		Daily Trip Tours per Person						χ^2 calc.	χ^2 tabl.
		0	1	2	3	4	5+		
Workers	model	4	22	12	4	1	0	1.0	7.8
	expected	4	25	10	3	1	0		
Mobile Widows	model	23	49	32	7	2	0	3.9	7.8
	expected	25	56	26	5	1	0		
Granny Flats	model	9	6	2	0	0	0	0.2	3.8
	expected	8	7	2	0	0	0		
Mobility Impaired	model	23	19	8	1	0	0	1.7	6.0
	expected	25	20	5	1	0	0		
Affluent Males	model	39	57	50	16	4	0	4.4	7.8
	expected	42	62	49	10	3	0		
Disabled Drivers	model	5	7	2	0	0	0	2.6	3.8
	expected	8	5	1	0	0	0		
All Clusters	model	103	160	106	28	7	0	3.8	9.5
	expected	112	175	93	19	5	0		

note: a 5 percent level of significance was used for χ^2 tabulated. Degrees of freedom range from 1 to 4.

of trip tours for these elderly respondents by 10.5 percent (484 versus 438). Recall that the model over estimated the number of trip tours from the base data set by 3.7 percent. However, the cluster distributions of the daily trip tours developed by the model are shown to fit the observed data quite well. All chi-square statistics are well below the threshold beyond which rejection of the null hypothesis is necessary. Figure 6.11 graphically depicts the tabulated data to illustrate the degree of fit between the model output and the observed data. Note that the scales for the y-axes of the plots vary from cluster to cluster.

The predicted and observed distributions of transportation mode use are presented in Table 6.25. The model generated values are shown to fit those extracted from the survey data reasonably well as evidenced by the statistically small chi-square values determined for all clusters. Note that the expected observations of transit trips had to be combined with the 'other' category to ensure that sufficient observations were used to determine the chi-square value. Furthermore, both personal and non-personal auto modes were combined for the determination of the chi-square values for the *Workers* and *Granny Flats* clusters.

6.5 Observations

The analyses presented in this chapter have shown that the modelling framework successfully replicated the Portland Metro base data. Furthermore, most of the model generated distributions of activity patterns and travel behaviour accurately represented the external data set from Vancouver, WA used for validation.

The analyses undertaken in support of the base model found that the distributions of all the model outputs (including daily activity patterns and travel variables) did not differ statistically from the distributions of the observed data. These findings suggest that the assumed linkages (e.g., the types of activities were conditioned on the total number of daily activities; the number of travel activities was conditioned on the total number of daily activities, etc.) may be appropriate.

One of the more significant measures of the model's output showed that the total number of trip tours was overestimated by only 3.7 percent for all of the elderly combined. An examination of the predicted trip tours by each cluster showed that the estimates differed by -9.6 to +9.0 percent of the observed values.

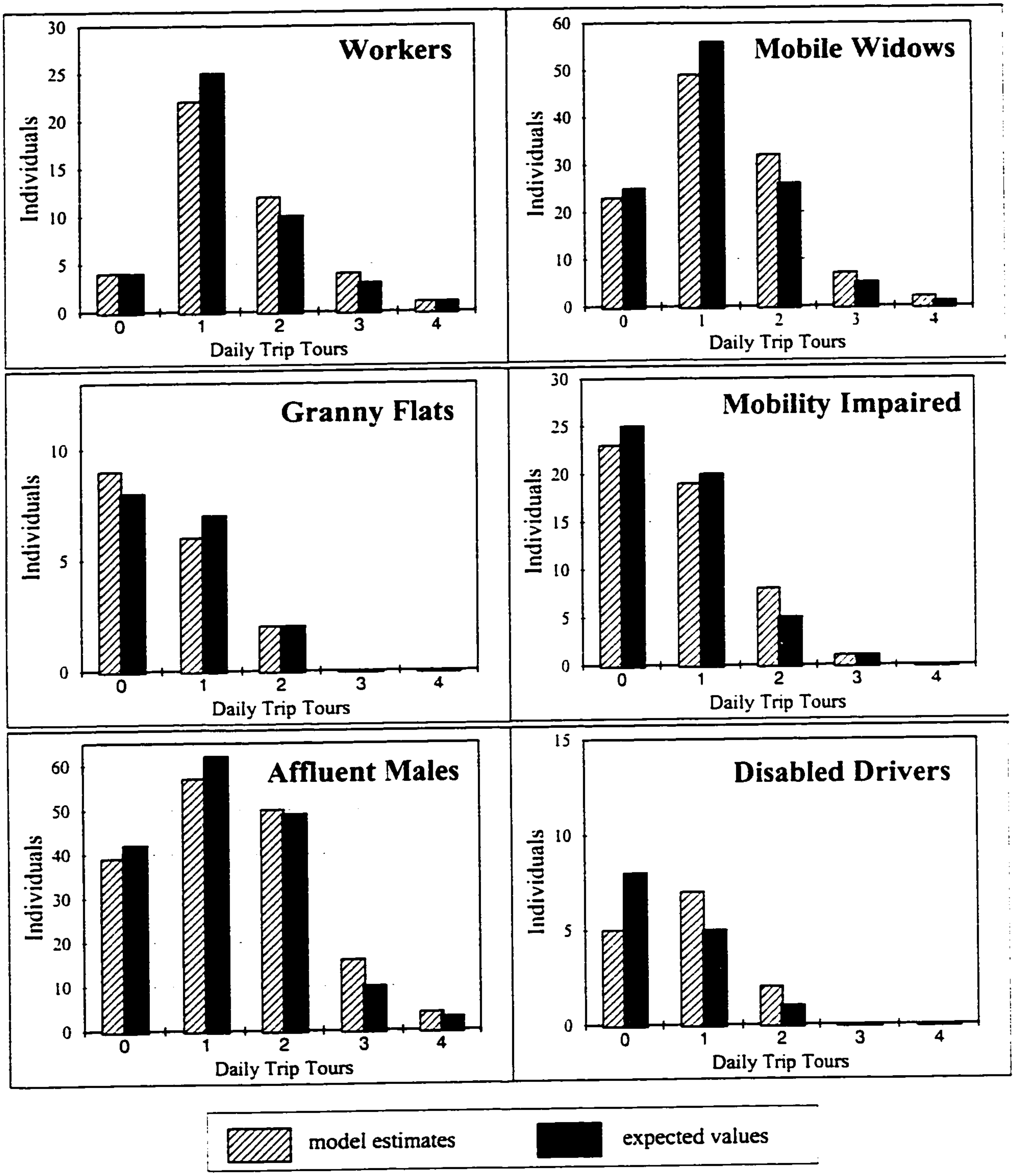

Figure 6.11: Total Daily Trip Tours -Model Fit for Vancouver, WA.

Table 6.25: Mode Split -Model Output for Vancouver, WA

Cluster		Trip Tours by Mode					χ^2 calc.	χ^2 tabl.
		auto (personal)	auto (non-personal)	walk	transit	other		
Workers	model	56	2	4	0	0	1.6	6.0
	expected	52	2	3	1	0		
Mobile Widows	model	114	11	13	3	1	5.4	7.8
	expected	109	7	10	1	1		
Granny Flats	model	8	0	1	0	1	1.4	3.8
	expected	9	1	1	0	0		
Mobility Impaired	model	12	10	8	7	1	2.2	7.8
	expected	13	7	6	6	1		
Affluent Males	model	193	6	17	2	3	2.6	7.8
	expected	179	4	15	1	3		
Disabled Drivers	model	8	0	1	0	0	0.7	3.8
	expected	6	0	1	0	0		
All Clusters	model	391	29	44	12	6	7.5	9.5
	expected	368	21	36	9	5		

note: a 5 percent level of significance was used for χ^2 tabulated. Degrees of freedom range from 1 to 4.

Perhaps the weakest component of the framework is the algorithms that were developed to estimate the daily number of trip tours based on an individual's itinerary of travel activities. The R^2 values of the cluster-specific models ranged from 0.65 to 0.93. An overall tendency for the models to overestimate the number of tours for those known to only have 1 was observed. Conversely, the models often underestimated the number of trip tours for those who actually undertook 3 or more. Although these trends might suggest an error in the specification of the functional form of the models, the Durbin-Watson tests did not detect any statistically significant serial correlation.

Another significant finding was that the assignment of travel activities to an individual could not be accomplished by relying solely on stochastic assignment. The consequence of using stochastic assignment was that the number of individuals who engaged in either very few or many activities away from home was underestimated. To correct this deficiency, the number of travel activities was allocated to each individual before the specific types of activities were assigned. Although the number of travel activities was pre-determined for each individual, the process of selecting the activity types remained stochastic.

The application of the model to the Vancouver, Washington data set validated that the model can estimate travel needs and demand with a reasonable degree of significance. The model-generated distributions of the number of daily activities, activities requiring travel, trip tours, and mode split were found not to be statistically different than observed data. However, the hypotheses that the distributions of assigned daily activities by class were no different from the observed data had to be rejected for three of the six lifestyle clusters. Similar results were found for the distributions of activities requiring travel. The number of activities requiring travel was overestimated by 9.2 percent for all of the elderly combined. It is unclear whether the differences in these distributions are a result of:

(1) Model mis-specification.
(2) Intrinsic differences in the characteristics of the Vancouver elderly.
(3) Small number of observations provided for each of the clusters by the Vancouver data set.

Nevertheless, the distributions of the number of trips tours that were estimated by the model were found not to be statistically different from the observed distributions. The resulting overall total number of trip tours were overestimated by the model by 10.5 percent. The differences likely result from the overestimation of the number of activities requiring travel and the inaccuracies of the base model. Five of the six cluster differences ranged from -9.1 to +15.2 percent of observed values. One cluster (the *Disabled Drivers*) was overestimated by 57.1 percent; however, the magnitude of this difference is the result of few observations (11 trip tours estimated compared with 7 observed).

CHAPTER 7

APPLICATIONS OF THE TRAVEL MODEL

Although the application of the model to the Vancouver, Washington data set in section 6.4 was undertaken to validate the framework, it also served to demonstrate the usefulness of the model for studying the general travel behaviour of the elderly. The values of key travel variables such as the number of daily trip tours, mode choice, and activities were estimated for members belonging to each of the elderly lifestyle groups. While this application of the model is useful, the framework's ability to deal with more focussed kinds of analyses is tested in this chapter.

The results of two exemplary applications of the microsimulation model are presented in subsequent sections. The tests were undertaken to demonstrate further the capabilities of the framework and to highlight how the products of the model can be used to interpret travel needs and behaviour. Furthermore, the incorporation of Module 3 (Adaptation Module) into the modelling framework is illustrated.

The first application of the model used the stated-adaptation responses to the road pricing survey conducted in conjunction with the Portland Metro activity-based survey (previously described in sections 3.1 and 5.1.2.3). The objective of this test case was to illustrate how the modelling framework can accommodate stated responses from a focused survey to forecast subsequent changes in travel behaviour.

The consequences associated with the implementation of a mandatory license retesting program for elderly drivers were studied as a second test application of the model. This case demonstrated the use of the modelling framework to identify the effects of a proposed policy targeted toward the elderly. The detailed travel needs of those who would potentially be adversely affected by the policy were identified.

7.1 Test Application 1: Stated-Adaptation to Road Pricing Scenarios

Although the stated-adaptation survey conducted as part of the Portland activity-based survey had a limited number of elderly respondents, the information was used to demonstrate how the model framework can incorporate stated response data. The model outputs described the changes in activity engagement and travel behaviour that could be expected if the proposed road pricing scenarios were to become a reality. A key attribute of the model is its ability to allow the comparison of impacts between lifestyle clusters. This facilitates the identification of groups with common socio-demographic characteristics who are more adversely affected by the proposed policies.

It was previously noted that there was a total of 64 elderly subjects who provided their expected adaptive behaviour associated with eight proposed scenarios of increased trip costs and corresponding congestion. resulting in 512 specific responses. The eight responses given by each subject refer to one specific activity type (i.e., meals, subsistence, etc.). Furthermore, three of the six lifestyle clusters (developed in Chapter 5) had very small samples resulting in insufficient representation to allow the responses to be segregated on this basis. Consequently, a fundamental assumption had to be made to use the data. The responses were aggregated and assumed to typify all clusters (see Table 5.10 for a comparison of responses between the clusters). If sufficient data existed, it would have been preferable to associate response patterns to each specific cluster (assuming they were, in fact, unique). The responses were. however, segregated based on the different activity classes given that they were relatively evenly distributed between the classes. Response patterns were developed for each specific activity type since elasticity presumably is lower for mandatory activities. Although the responses were aggregated among the clusters, there would still be consequences unique to each cluster given different levels of involvement in each class of activities and different propensities for travel.

The specific stated-adaptation responses which were quantified to modify the base model (developed in Chapter 6) included:

(1) Make trip less often.
(2) Combine trip with others.
(3) Do activity at home.
(4) Not make trip at all.

Other responses which could not be used, given the limited scope of the developed model, included:

(1) Make same trip at different time of day.

(2) Look for similar destination closer to home.

A modelling framework that includes spatial and temporal attributes of activity engagement would be required to incorporate these kinds of behaviour modification.

The simplistic structure of the stated-adaptation survey precluded a more comprehensive understanding of the respondents' behaviour modification in response to the pricing scenarios. All replies given by an individual referred to a single specific activity in which they had previously been engaged. Allowing the respondent to modify their whole daily activity itinerary in response to the proposed road pricing scenarios would have been more appropriate. A survey technique such as the HATS method (discussed in section 2.2.2) would have provided a much more thorough description of the adaptive behaviours among the respondents. For example, when the stated adaptation is to *combine the trip with other trips* it would be useful to more fully understand how the activity itinerary is repackaged into trip tours. Vague responses such as *make trip less often* do not allow for a quantification of the reduction in trip tours. Nevertheless, assumptions were made to allow the data to be applied within the model structure.

It was previously noted that an adaptation module could modify the algorithms imbedded in either Module 2 (Development of Daily Engaged Activity Patterns) or Module 4 (Development of the Number of Trip Tours). For the first test case, the responses of *make trip less often, do activity at home,* and *not make the trip at all* were used to modify Module 2, while the response of *combine trip with others* was applied to Module 4.

Since the response of *make trip less often* was not quantified, it was necessary to assume that, on average, actual adaptive behaviour would result in the activity being engaged in 25 percent fewer times. This value was subjectively chosen for illustrative purposes. To exemplify how this response was used to modify the model the following illustration is given. When a social activity was the subject of the stated-adaptation responses, 17.5 percent of the respondents said they would choose to travel to engage in the activity less often when faced with the scenarios of increased road pricing. Therefore, the frequency of engagement had to be reduced by 4.4 percent (25 percent reduction for 17.5 percent of respondents). This reduction could have been made either by modifying the cumulative distribution functions coded into the model programming (section 6.2.3) or as an add-on utility that stochastically eliminates social activities from the itinerary developed for each individual. The modifications to the model for the response of *not make trip at all* were made in a similar way. For example, 12.5 percent of responses for recreational activities were not to make the trip at all. Consequently, the occurrence of this activity (when it required travel) was reduced by a corresponding amount for all clusters.

The response of *do activity at home* required that some activities be recoded to reflect that they no longer required travel away from home. For example, 16.1 percent of the stated adaptations for a meal were to engage in the activity at home rather than be exposed to the increased travel cost and congestion scenarios. The activity itineraries assigned to each individual were reviewed and if a meal requiring travel was present there was a 16.1 percent probability that it would be converted to a meal to be taken at home. Because of this specific response, it was necessary to evaluate the impacts of the proposed policies on both total daily activities and only those requiring travel. Since some types of travel activities are more likely to be substituted by a similar activity engaged in at home, some clusters were expected to show a greater reduction in their itinerary of travel activities than in total daily activities.

When a respondent said that they would likely *combine trip with other trips*, the resulting number of daily trip tours would be affected. To incorporate this response into the model, the regression equations developed in section 6.3 had to be modified to account for the decreased propensity for trip-making. Each activity class had a different probability associated with it of combining with other activities to aggregate trip tours. For example, from the survey it was found that 7.1 percent of the respondents said that they would adapt to higher transportation costs by combining a meal with other activities to form one less trip tour. Consequently, the base data set used to develop the regression equations was modified by reducing the number of activities requiring travel within each activity class. The regression equations were then refitted to the data and the corresponding coefficients changed in the model programming.

With the model programming changed to reflect the adaptive behaviours associated with the road pricing scenarios, the simulation model was rerun for 1,150 individuals, representative of the base data set. The model outputs were then compared with the actual observed activity patterns and travel behaviours of the respondents recorded in the base survey.

Figures 7.1 and 7.2 illustrate the projected changes in activity patterns among the elderly that would result if the road pricing scenarios were implemented. Note that the plots in Figure 7.1 aggregate all of the elderly lifestyle clusters. All activities (not just those requiring travel) are depicted since some individuals will adapt by engaging in an activity at home rather than away. The plots labelled 'stated-adaptation' represent the outputs of the model which incorporates the behaviour modifications expressed in the stated-adaptation survey. The 'base data' plots simply represent the observed behaviour captured by the Portland activity-based survey. As shown, there is an increased propensity to engage in relatively few activities (1 to 5 per day) and, conversely, a decrease in the proportion who engage in more than 6 activities per day. Clearly, the elderly have indicated that the prospect of increased transportation costs will likely result in a decrease in overall activity engagement. In fact, the data suggest that the average number of activities the elderly engage in per day would drop from 7.29 to 6.68.

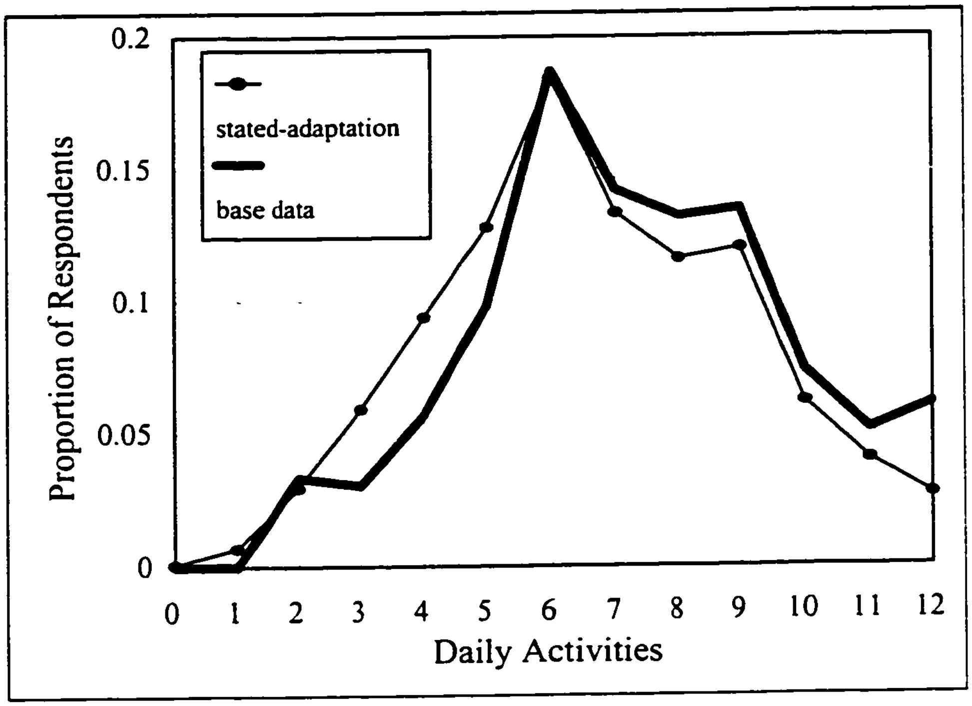

Figure 7.1: Daily Number of Activities -All Clusters

The corresponding changes in overall activity engagement for each of the six lifestyle clusters are presented in Figure 7.2. The same general trend depicted in Figure 7.1 is present for most of the individual clusters. Recall that the stated adaptations were not segregated on the basis of clusters, only on activity type, so any differences in trends would be solely attributed to differing patterns of activity engagement between the clusters (refer to Table 5.8). If the true response patterns for specific activities are indeed significantly different between clusters, then the model estimates may be misleading.

Members of the *Workers* cluster were found to be the most elastic in response to the road pricing scenarios. The average number of daily activities for this group dropped by more than 17 percent. However, this finding may be overestimated because there were few responses to the survey which included subsistence activities. A general observation is that those who have transportation restrictions or dependencies (i.e., the *Granny Flats, Mobility Impaired,* and the *Disabled Drivers*) were found to modify their activity itineraries the least among the elderly. Interestingly, the *Granny Flats* and the

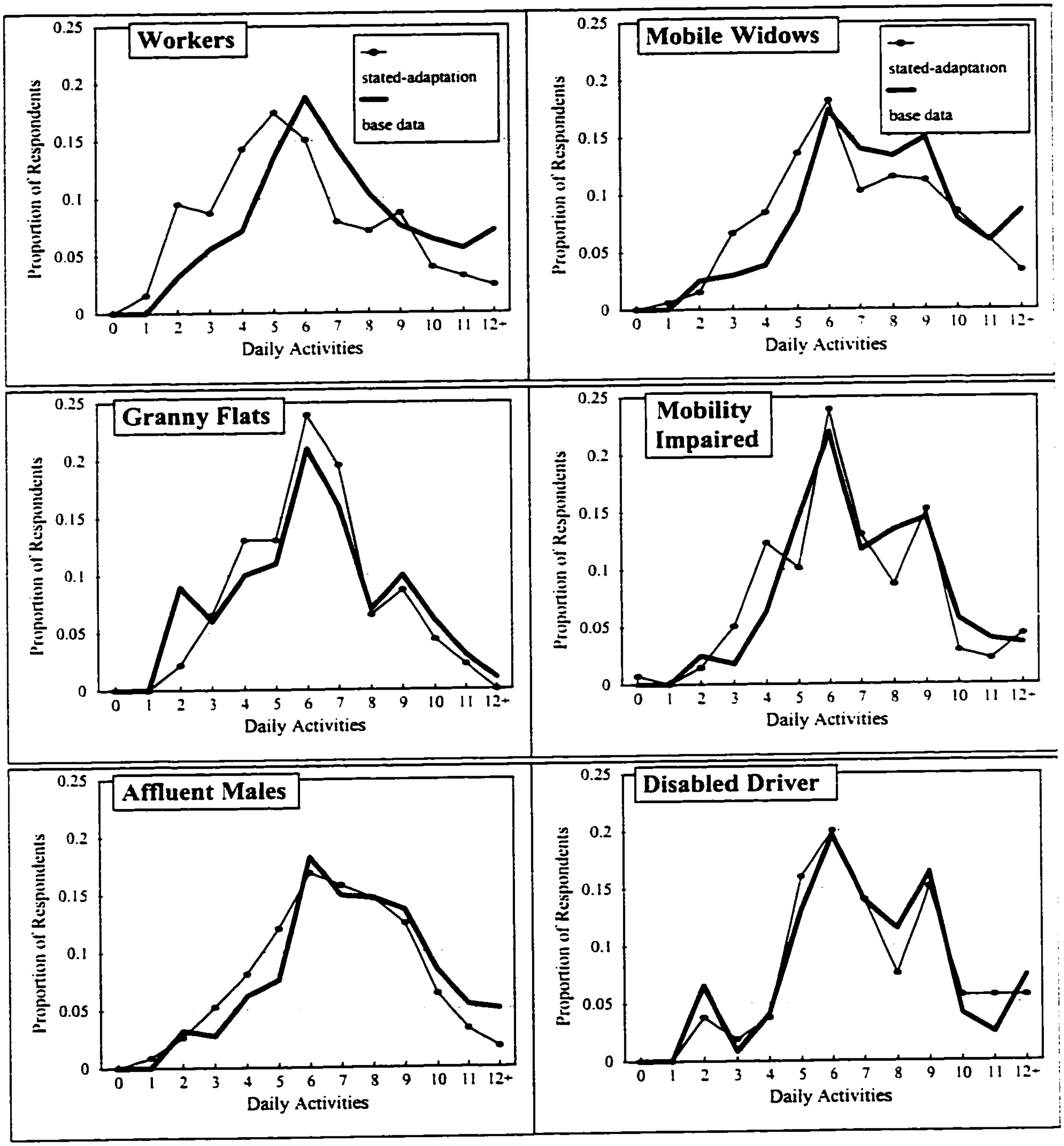

Figure 7.2: Daily Number of Activities by Cluster

Disabled Drivers were found to reduce their average number of daily activities by only 0.2 and 0.4 percent, respectively. These findings reflect the fact that members of these clusters travel to activities much less than others and may therefore inherently be less influenced by increases in travel costs. Conversely, those who are relatively independent with respect to mobility were shown to be more elastic in response to increases in road pricing. The *Mobile Widows* and the *Affluent Males* were found to reduce their average daily number of activities by 9.0 and 8.0 percent, respectively.

Figure 7.3 depicts the expected change in the number of activities requiring travel resulting from the increases in transportation costs. The trend is similar to that depicted in Figure 7.1. It is shown that a greater proportion of the elderly are projected to engage in one or no activities which require travel while there is a general decrease in the number who will engage in two or more activities away from home. The number of daily activities that require travel is expected to drop from an average of 2.87 to 2.11 (or 26.4 percent) in response to the road pricing scenarios.

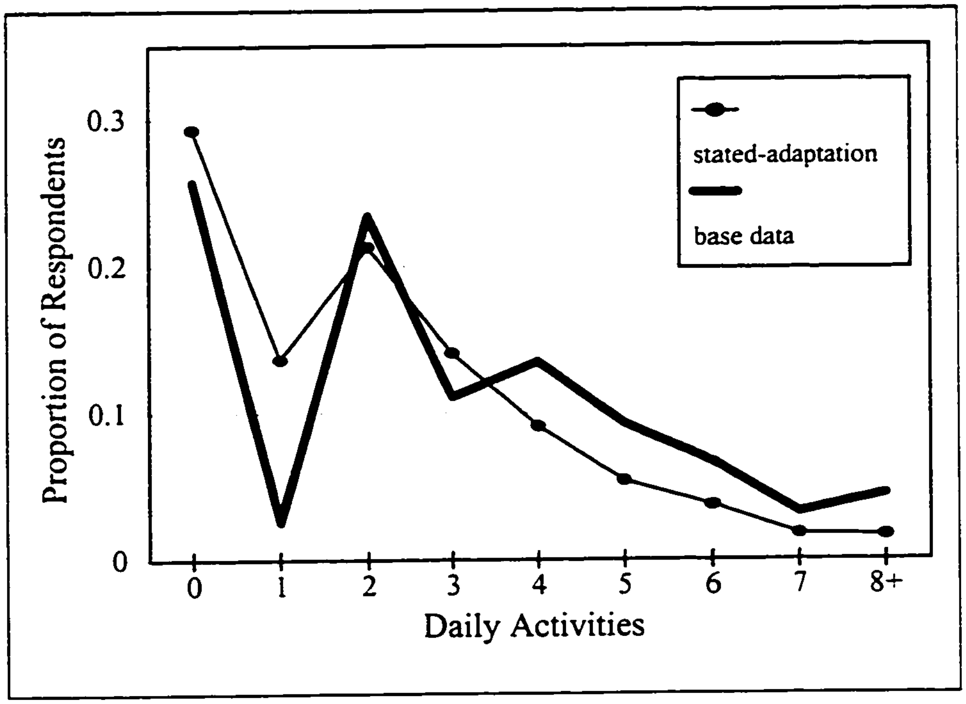

Figure 7.3: Daily Number of Activities Requiring Travel -All Clusters

Figure 7.4 presents the same information as that in Figure 7.3 except the plots are segregated by lifestyle cluster. As shown, the trend toward fewer activities away from home is a prevalent consequence of the road pricing scenarios. Overall, the differences between clusters are less dramatic than those depicted in Figure 7.2 which included all activities despite whether travel was required or not. Reductions in the daily number of activities engaged in away from home ranged from 35.9 to 23.8 percent for the *Workers*

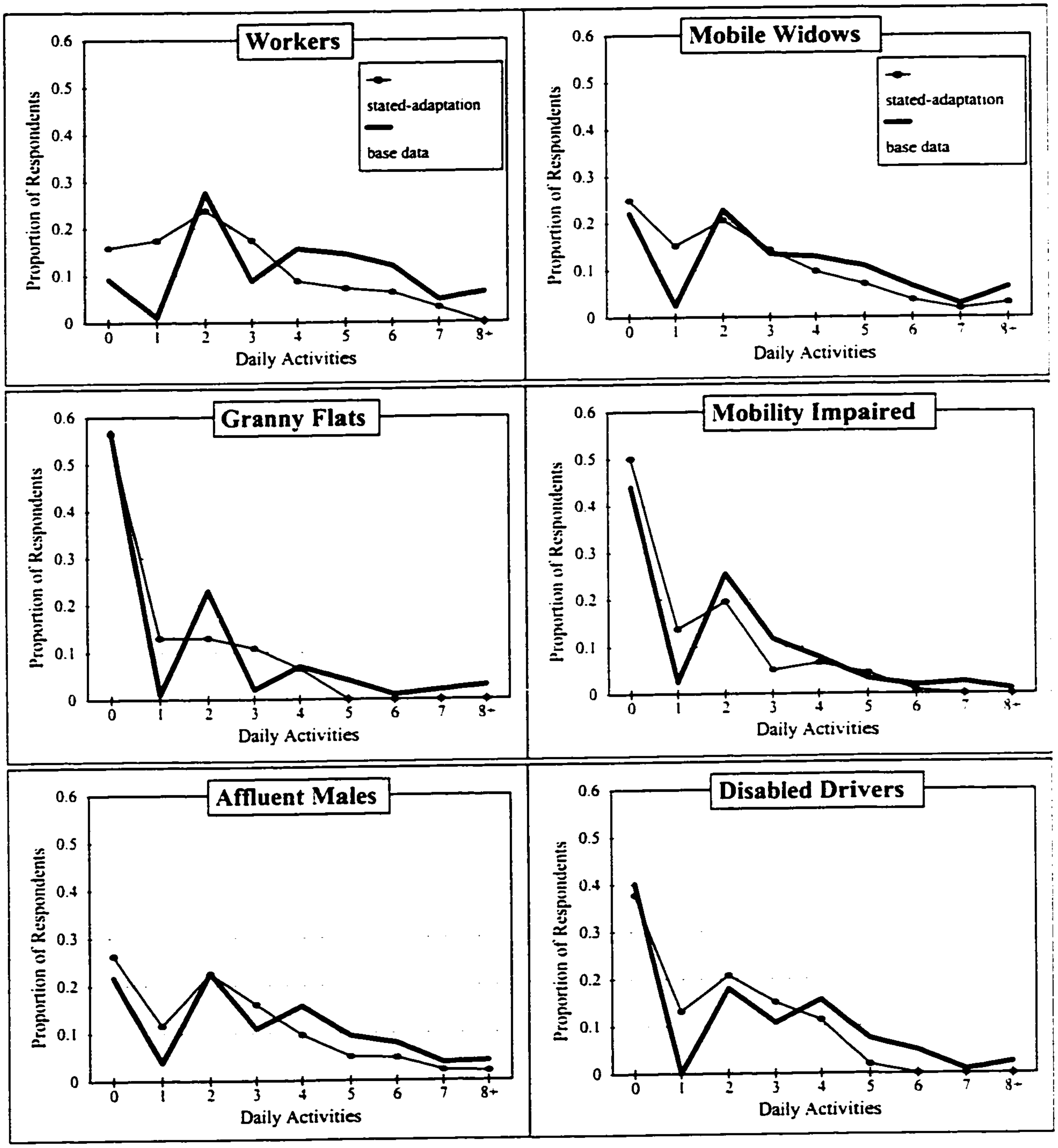

Figure 7.4: Daily Number of Travel Activities by Cluster

and the *Affluent Males* clusters, respectively. Although the *Granny Flats, Mobility Impaired*, and the *Disabled Drivers* clusters were previously found to reduce their overall daily activity itinerary relatively little, they were found to reduce their travel activities by 33.3, 30.2, and 31.4 percent, respectively. These seemingly contradictory trends prevail when members of these groups substitute a travel activity for one at home. For example, members of these clusters often travel to engage in activities such as meals, household maintenance, and amusement which are the three activity classes most likely to be undertaken at home in response to increased travel costs.

The effect of the proposed road pricing scenarios on the engagement of different activity types is presented in Figure 7.5. The data depicted in the plot are for the 1,150 elderly individuals processed by the simulation model ('stated-adaptation' plot) and for the same number of respondents from the activity-based survey ('base' plot). Not surprisingly, engagement in meals, amusement, and recreational activities requiring travel is projected to decline substantially. The projected change for subsistence activities is highly suspect given the small number of stated-adaptation responses for this class of activity. Figure 7.5 indicates a relatively large decrease in subsistence activities in response to the road pricing scenarios. Actual behaviour would likely be much more inelastic. Interestingly, there are only small changes in participation in the activity classes of household maintenance, social, and other.

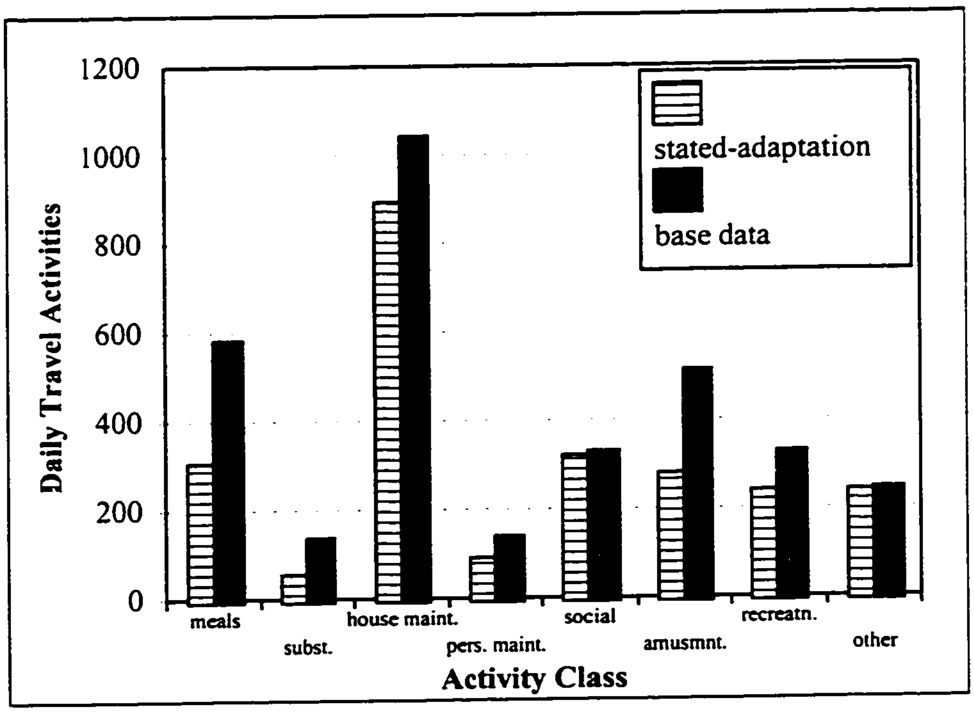

Figure 7.5: Daily Travel Activities by Activity Class -All Clusters

An overall reduction in the number of daily trip tours is an expected consequence of the road pricing policies since the adaptive behaviours include a decrease in the number of activities engaged in away from home and the amalgamation of trip tours. The model-generated estimates that quantify these reductions are depicted in Figures 7.6 and 7.7. As shown in Figure 7.6, it is expected that a greater proportion of the elderly will either not travel or make only one trip tour on a given day. Furthermore, there is a significant reduction in the number who will undertake multiple trip tours on a daily basis. The data show that for the elderly the number of daily trip tours among the elderly will drop from an average of 1.12 to 0.82 in response to the road pricing scenarios.

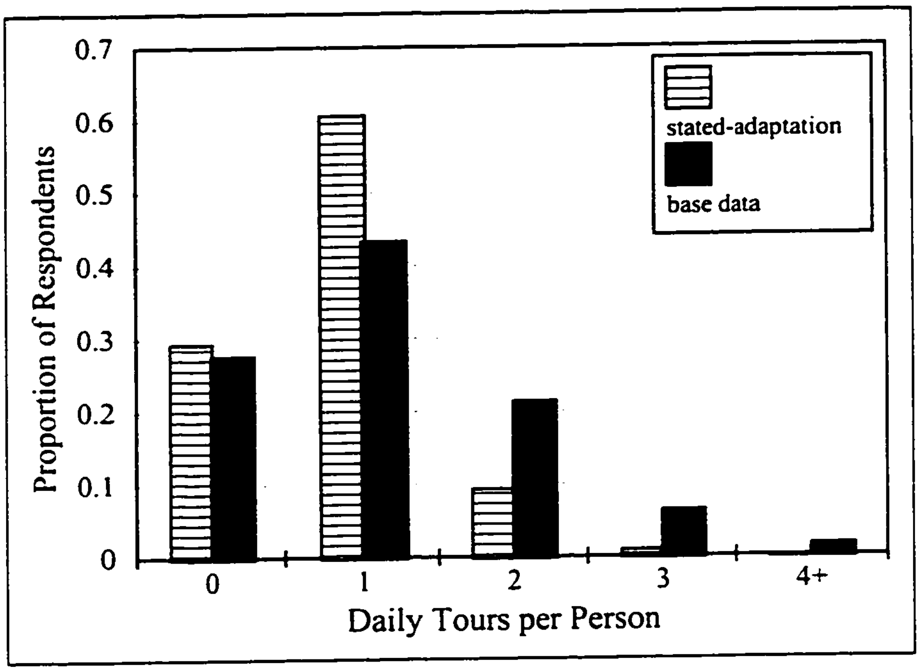

Figure 7.6: Daily Tours per Person -All Clusters

Similar patterns of reduced trip-making are evident among the six elderly lifestyle clusters depicted in Figure 7.7. Again, any changes in patterns are solely the consequence of the activity patterns associated with each lifestyle cluster. The *Workers* were found to reduce trip-making the most in response to the road pricing scenarios. Their average number of daily trip tours were predicted to drop from 1.44 to 1.00 (or 30.6 percent). Th *Disabled Drivers* were found to be the least elastic reducing their daily trip tours from 0.82 to 0.66 (or 19.5 percent).

While the preceding analyses have provided insight into how the model can accommodate the results of surveys that solicit stated adaptations or stated responses from individuals, the actual results would have much more insightful had there been sufficient data to allow specific response patterns to be

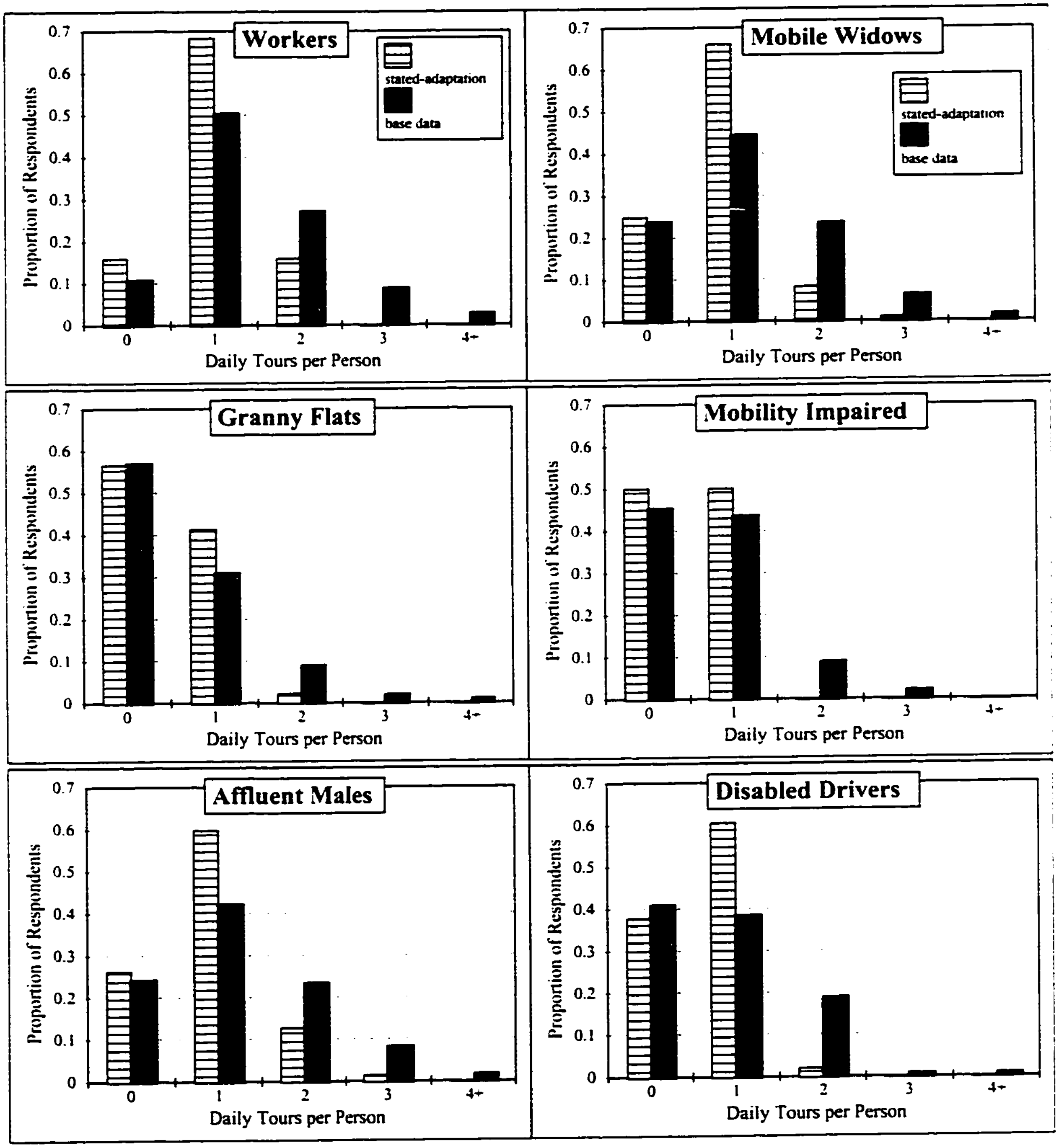

Figure 7.7: Daily Tours per Person by Cluster

associated with each cluster. This would have provided a more thorough estimate of how the proposed policies might have different levels of impact for each cluster. Nevertheless, estimates of the impacts have been developed for elderly as a whole. Furthermore, the analyses have successfully illustrated how an Adaptation Module can be incorporated into the modelling framework.

7.2 Test Application 2: Mandatory Retesting for Elderly Drivers

The second test application of the model illustrated how it might be used to examine the implications of establishing a policy of mandatory retesting for the renewal of drivers' licenses. The model outputs would give an agency a better understanding of the trip-making behaviour and travel needs of those who might be forced to surrender their driving privileges. This, in turn, would provide a better understanding of the consequences of such a policy and assist with the assessment of possible mitigative measures (e.g., subsidized public transportation programs, dial-a-bus, etc.) to meet travel needs. It was not the intent to predict which individuals would be forced to suspend their driving; rather the activity engagement patterns and trip-making characteristics are identified for an elderly subgroup who exemplify those who would likely lose their license.

The first step in applying the model to test this policy was to establish criteria which can be used to delineate a subgroup of the elderly who are most likely to lose their driving licenses through a retesting program. To proceed with the application of the model, the different levels of screening processes used by agencies needed to be understood. While many jurisdictions have contemplated mandatory retesting, the policies that have been developed lack uniformity between provinces. A survey undertaken by Hildebrand (1989) found that license renewal was essentially automatic for the elderly in Prince Edward Island, Nova Scotia, New Brunswick, Manitoba, and Saskatchewan. The remaining provinces and territories typically only require an annual or biannual medical check beginning at age 70 to 80 years. However, the province of Ontario has established a mandatory vision and written test which must be successfully completed at the age of 80 and every second year thereafter. No statistics have been kept in Ontario to quantify the percentage of elderly that was forced to surrender their license because of the screening program. However, it has been estimated that an attrition rate of approximately 10 percent exists at the threshold age of 80 years (Tesca, 1998). Unfortunately, little is known about the characteristics of the elderly who retired from driving because of retesting.

It is important to recall that the segregation basis of the lifestyle clusters must be directly related to the final use of the model. If, for example, age and health are the only predictors of who would pass an examination for relicensing, then the clusters developed in Chapter 5 should have been established based on different variables for this particular application. To apply the model as developed, it would have been necessary to identify those who typically fail retesting based on the socio-demographic characteristics identified in Table 5.7. If socio-demographic characteristics were known from past experiences, then the expected proportions within each lifestyle cluster could have been determined using cluster identification. Nevertheless, for illustrative purposes, the subgroup of drivers who would potentially lose their license was delineated simply as a fraction of those 80 years of age or older. The only other criterion was, of course, that they currently hold a driver's license.

Although age and the presence of a driver's license are dimensions of the lifestyle clusters, they are only two of ten socio-demographic variables used to define the groups. Consequently, some members of all six lifestyle groups would potentially be affected by a retesting program. The base data set was reviewed to determine the percentage of members who were 80 years of age and older and licensed to drive. The results are presented in Table 7.1. Since none of those who belong to the *Mobility Impaired* cluster were licensed (see Table 5.7) they were excluded from further consideration. It is interesting that only 16 percent of those in the *Granny Flats* cluster were found to fit the criteria since this group had the highest average age of 78.0 years (Table 5.7). However, given that only 48 percent of the group members hold a driver's license, fewer members than expected would be affected by a proposed retesting program.

A sample of individuals was processed by the simulation program in proportion to the percentages outlined in Table 7.1. The subsequent aggregation of outputs was then used to represent a profile of activity and travel behaviour for those who would be adversely affected by a retesting program.

Table 7.1: Distribution of Licensed Elderly 80 Years of Age and Older

Cluster	Percentage Over 80 Years and Licensed
Workers	5.6%
Mobile Widows	16.6%
Granny Flats	16.0%
Mobility Impaired	0.0%
Affluent Males	10.5%
Disabled Drivers	24.6%

The results of the simulation run are presented in Table 7.2. As shown, the model outputs are contrasted with the averages from the 'base data' for those who are licensed and more than 80 years of age as well as all of the elderly. The 'base data' presented in the table represent observed values derived from the Portland data set that the model was founded on. Generally, the model outputs are shown to provide closer estimates than those of overall averages for the elderly. The differences between the model outputs and the observations (for those more than 80 with a license) can be attributed to the aggregation of characteristics which is inevitable for a categorically structured framework. For example, the 5.6 percent of the *Workers* who are 80 years and older likely travel less than the other cluster members as a whole.

Table 7.2: Travel Characteristics of Licensed Elderly 80 Years of Age and Older

Variable	80+ Years with License Simulation Model	80+ Years with License Base Data Set	All Elderly Base Data Set
Daily Trip Tours	1.01	0.88	1.12
Daily Travel Activities:			
Total	2.61	2.17	2.87
meals	0.42	0.39	0.50
subsistence	0.08	0.09	0.12
house maint.	0.86	0.64	0.90
personal maint.	0.11	0.08	0.12
social	0.26	0.27	0.28
amusement	0.40	0.37	0.45
recreation	0.26	0.23	0.29
other	0.21	0.10	0.21
Modes:			
personal auto	79.6%	78.6%	80.0%
non-personal auto	8.5%	8.3%	6.2%
walk	9.2%	10.0%	9.4%
transit	1.8%	0.6%	3.2%
other	0.9%	2.5%	1.2%

It is important to realize that the model estimates would be more accurate if the target groups could have been identified from more than two of the socio-demographic variables used for cluster delineation. For example, the presence of a disability (one of the lifestyle cluster dimensions) might be shown to be an indicator of those who would lose their license. Similarly, one's relation to the household head (another cluster dimension) may also contribute to the predictability of who retires their license since some individuals may more readily or voluntarily surrender their license if they have a spouse to provide transportation.

Table 7.3 presents a summary of the characteristics associated with trip-making made by those 80 years and older as the drivers of an automobile. Consequently, these characteristics describe the typical activities which would be affected should an elderly driver be forced to relinquish their driver's license. Both the model predicted and observed values are presented in the table.

Table 7.3: Characteristics of Activities Accessed by Driving

Variable	80+ Years with License Simulation Model	80+ Years with License Base Data Set
Daily Trip Tours	0.58	0.36
Daily Travel Activities:		
Total	1.60	0.94
meals	0.26	0.19
subsistence	0.06	0.05
house maint.	0.53	0.26
personal maint.	0.07	0.04
social	0.15	0.12
amusement	0.25	0.16
recreation	0.15	0.09
other	0.13	0.04

It is seen that the model generated values are consistently higher than observed values. This is likely the result of aggregation errors caused by grouping the very old (80 years and older) with younger individuals in lifestyle clusters. Again, it is illustrated that the basis for cluster segregation should be closely linked to the final use of the model. In other words, the model would have generated results which more closely resembled observed values if more variables could have been used to identify those likely to surrender their driver's license when subjected to a retesting program.

The preceding tables have profiled the travel and activity patterns of those who would lose their driving privileges because of mandatory retesting. However, the significance of this loss to individuals and probable adaptations can only be informally estimated on the basis of cluster membership. Adaptive behaviours could include the use of alternative modes (e.g., public transportation, walk, etc.), alternative roles (e.g., passenger in an automobile), and the rescheduling, substitution, or elimination of the activity. Insight into possible adaptations can be achieved by reviewing typical characteristics of cluster members. For example, the members of the *Mobile Widows* cluster are less likely to have a spouse or other household member who can provide an alternative means of personal transportation. Conversely, most of those assigned to the *Granny Flats* cluster likely have a family member who can fulfill some transportation needs given that the average household size is 3.26 (see Table 5.7). The use of traditional public transportation as a substitute may have limited application for those belonging to the *Granny Flats, Mobility Impaired,* and *Disabled Drivers* clusters since many have disabilities significant enough to affect travel.

The prevalence of some adaptations, including being driven by non-household members, is probably best estimated using stated or revealed adaptation information. Although typical activity profiles are known for those affected, the model framework is restricted in its ability to estimate the extent of activities that will be eliminated as an adaptive response. Knowing which travel activities are mandatory and discretionary provides some insight into how many might be eliminated or replaced with a substitute activity at home. Again, stated-response surveys coupled with the model outputs would provide a much broader understanding of the implications of this policy.

7.3 Observations

The preceding test cases have illustrated some of the inherent strengths and weaknesses of the modelling framework when it is used for focussed applications. The identification of travel needs, including trip tours and the corresponding activities, is the primary benefit afforded by the model. The division of the elderly into lifestyle clusters gives the analyst the ability to contrast different behaviours and reactions among the various groups.

The first test case illustrated the need to provide statistically significant representation for each of the predefined clusters if external data are to be applied to the model. The responses to the stated-adaptation survey were used to modify the distribution functions of the model, however, insufficient samples were available for each cluster. To ensure adequate coverage for future applications, a stated-response survey could be designed to employ a stratified sampling scheme.

The second test application showed that when a specific target group among the elderly is studied, the lifestyle cluster structure delineated in Chapter 5 may, or may not, be appropriate. The target group for that analysis was the elderly who were 80 years of age and older and had a driving license. The results showed how travel characteristics can be diluted when individuals are aggregated into clusters that are defined using multiple dimensions. This does not negate the model framework, it simply shows that other versions using different cluster structures may be more appropriate for some applications.

The model structure requires that, in most cases, the socio-demographic characteristics of the target group being studied be known a priori so that membership in each lifestyle cluster can be estimated. If this is not possible, the clusters would likely need to be delineated on the variables which identify the target group. For example, if the model were to be used to study changes in a transit system, the existing format of the model could provide some characteristics of individual transit trips and the trip-makers. The types of activities associated with each trip can be estimated as well as the corresponding socio-demographic characteristics of the trip-makers. Note, however, that the socio-demographic characteristics are limited to cluster averages since only the cluster membership is known for each individual undertaking the trip. This kind of information would provide an agency with a general description of who would be affected by changes in operating policies and to some extent, how they would be affected. If, however, more detail is required, it might be more appropriate to develop the clusters including dimensions to delineate those who use public transportation. Clusters may be developed which differentiate those who are captive to public transportation from those who have alternative means, for example. Furthermore, it is possible that more detailed information concerning scheduling and routing, for example, may be required. In this case, an activity-based model which identifies temporal and spatial attributes to activities would be necessary.

CHAPTER 8

CONCLUSIONS AND RECOMMENDATIONS

This chapter highlights the study's principal findings derived from preceding analyses and summarizes some recommendations for future research in this field. The primary objectives of the research were to provide a fuller understanding of the travel behaviour and needs of the elderly and to synthesize their trip-making by developing a simplified activity-based model. These goals were achieved through a series of analyses that focussed on the results from an activity-based survey which included 1,150 elderly respondents.

8.1 Conclusions

Although each chapter describes the results of analyses in detail, the more significant conclusions attributed directly to this research are highlighted below. The findings are delineated into three main subject areas dealing with the characteristics of activity engagement and travel behaviour of the elderly, cluster analyses, and model development and testing.

8.1.1 Characteristics of Activity Engagement and Travel Behaviour of the Elderly

The following conclusions were developed from the descriptive analyses undertaken primarily to contrast the activity and travel patterns of the elderly with younger age groups. Results are derived from the responses to the Portland activity-based survey.

(1) Although elderly age groups showed a slight increase (over younger groups) in the daily number of activities they engage in, beginning at about age 75 a marked reduction in the number to which they travel was observed. For example, those over 75 engaged in 10.7 percent

more daily activities than their middle-aged (35 to 55 years) counterparts, yet they travelled to 45.0 percent fewer activities.

(2) Household maintenance activities were found to be the primary reason for travel among elderly age groups. This activity accounted for approximately 40 percent of all trips away from home which is a larger proportion than for those in younger age groups who average less than 25 percent.

Social activities accounted for an increasingly larger proportion of travel activities for those beyond the age of retirement. This activity class only represented approximately 8 percent of all activities requiring travel for the middle-aged groups, however, it accounted for 12 to 18 percent for those over 65 years of age.

(3) The average number of daily trip tours for those aged 65 to 75 increases to approximately 1.2 (from around 1.0 for those who are middle-aged), then steadily decreases to about 0.6 for those 85 and over.

(4) Beyond about age 65, the average number of activities per trip tour steadily decreases with advancing age. For example, those aged 65 to 69 average 1.68 activities per trip tour, while those 85 and over only average 1.29. Despite this finding, total trip distances appear to remain consistent across all age groups.

(5) The very old (85 years and older) showed an increased propensity to walk to activities away from home with a corresponding decrease in auto use. Younger groups were shown to undertake approximately 9 percent of trips by walking, while those 85 and over averaged 20 percent.

(6) The percent of elderly who travel as automobile passengers steadily increases with advancing age. The middle-aged groups average 11 percent of trips as passengers, however, this proportion jumps to 20 percent for the 60 to 65 age group. The proportion increases for each successive age group to a maximum of 40 percent for those 85 years and over. This trend is consistent with the steep decline in the proportion who maintain a driver's license as they get older.

8.1.2 Cluster Analyses

The conclusions derived from the series of cluster analyses undertaken to delineate lifestyle groups among the elderly are listed:

(1) Three approaches to cluster analysis were based respectively on activity engagement, socio-demographic, and travel behaviour. Despite the approach used, the optimal number of subgroups was found to range from five to eight.

(2) The final cluster set developed based on travel behaviour variables identified seven subgroups with unique travel characteristics. The groups included 8 percent of the total who rely on modes other than the automobile, 18 percent who travel exclusively as passengers in automobiles, 15 percent who make frequent local trips as drivers, 34 percent who make infrequent local trips as drivers, 4 percent who regularly engage in journeys far from home, 8 percent who often walk or drive to their destination, and 14 percent who seldom travel from home. Of the three approaches used for cluster analysis, this solution set provided the weakest partitions in activity patterns but the second strongest discrimination across socio-demographic variables.

The ability to associate an individual with a predefined cluster using commonly available data was a prerequisite for the model structure. For the travel behaviour clusters, only 38 percent of individuals could be identified with their appropriate group using commonly available socio-demographic variables.

(3) Of the three approaches used for cluster analysis the six groups delineated using socio-demographic variables were found to provide the second strongest partitions in activity and travel behaviour variables. Clusters delineated consist of 11 percent of all the elderly who are characterized as those who continue to work, 4 percent who live with their offspring, 12 percent who are mobility impaired, 5 percent who drive despite being disabled, 29 percent who are widows, and 38 percent who are affluent and typically male. A distinct advantage of this approach was that individuals whose cluster membership is unknown could be properly allocated to each cluster based on commonly available socio-demographic information.

(4) The five clusters developed using dimensions of activity engagement delineated subgroups including 7 percent of the elderly who are still active in the workforce, 37 percent of the

elderly who are active socially, 6 percent who often engage in recreational pursuits, 20 percent who undertake a disproportionate amount of shopping, and 30 percent who are relatively inactive. Although strong partitions were developed in activities requiring travel, many trip-making characteristics and socio-demographic variables were found not to vary significantly between groups. Only 29 percent of individuals could be identified with these clusters based on socio-demographic information.

(5) When any of the three approaches were combined to identify clusters (e.g., if both socio-demographic and travel behaviour variables were used to segregate clusters), the resulting subgroups provided weak delineations across most dimensions. Clustering on too many varied dimensions weakened the ability to identify subgroups with homogeneous characteristics.

(6) For the general study of elderly travel behaviour, clusters defined with socio-demographic variables provided optimal groupings for the basis of the modelling framework. If the model is to be applied for a more focussed application, segregating individuals on different dimensions may be necessary.

8.1.3 Model Development and Testing

Conclusions drawn from the development of the activity-based microsimulation model fall into one of two categories. They refer either to the relationships developed in support of the model algorithms, or to the ability of the framework to predict travel behaviour.

(1) Background analyses undertaken in support of the simulation model showed that only two lifestyle clusters had distributions of the total daily number of activities that were statistically different from the overall distribution. However, all but one cluster were found to have statistically different distributions of the percent of activities requiring travel compared with the distribution for all of the elderly combined.

(2) The numbers of daily trip tours for individuals were estimated using equations developed for each cluster through ordinary least squares regression. Independent variables were the number of activities requiring travel from each of the eight activity classes. The R^2 fit of the equations ranged from 0.65 to 0.93 for the six clusters.

(3) The model framework developed through this study successfully replicated all facets of the base data used for its development. Elements of travel behaviour that were synthesized included total daily activities (with and without travel), activities engaged in by class (with and without travel), total daily trip tours per person, and mode splits. The model generated estimates of the daily number of activities requiring travel differed by no more than 11.6 percent of the observed values for each lifestyle cluster. For all of the elderly combined, the model overestimated the number of daily travel activities by 3.7 percent. The predicted number of total trip tours for each of the six lifestyle clusters was no more than 9.6 percent different from the observed values. Trip tours were overestimated by 3.7 percent for all of the elderly combined.

(4) The model capabilities were evaluated by simulating behaviour in Vancouver, WA. The model-generated distributions for the number of daily activities, activities requiring travel, trip tours and mode split were found not to be significantly different from observed data. However, the distributions of activities by class could not be shown to be statistically similar to the observed distributions of three clusters. The validation showed the model to overestimate the number of activities requiring travel and the number of trip tours for the entire elderly group by 9.2 and 10.5 percent, respectively.

(5) The model was applied to test the affect of a series of proposed road pricing scenarios on elderly behaviour. It was estimated that there would be a 26 percent reduction in the number of activities engaged in away from home resulting in a 27 percent decrease in the number of trip tours undertaken. Individual clusters were shown to reduce their average travel activities from 23 to 36 percent, while reductions in trip tours were ranged from 19 to 31 percent. This test case illustrated the need to represent each lifestyle group statistically if information from a stated-response survey is to be successfully incorporated in the model.

(6) The second test case the model was applied to dealt with the effect of a mandatory retesting program for drivers' licenses. The model was used to examine the travel and activity characteristics for those more than 80 years old who were licensed. The model predicted values for variables such as daily trip tours and activities requiring travel were consistently higher than observed values. Any differences were the result of aggregation errors caused by grouping the very old with younger individuals in lifestyle clusters. This test case illustrated that the most effective analysis of certain policies may require the definition of clusters on related dimensions.

8.2 Recommendations

Although this study has made several significant contributions, much work is still needed concerning elderly travel needs and activity-based modelling. The following recommendations are suggested as an extension of the work undertaken:

(1) A series of cluster analyses of elderly responses to other activity-based surveys should be undertaken to learn if similar subgroups to those found in Chapter 5 can be delineated. An underlying premise to the research is that subgroups with similar characteristics exist in different geographic areas, although the proportions within each group will likely vary.

(2) The cluster analyses undertaken in this study relied on two-day activity-based surveys. Performing the same analyses with activity-based information collected over a longer period (say one or two weeks) would be interesting. It is quite possible that subgroups with different characteristics would emerge as longer term behaviour is observed.

(3) Valid comparisons of responses to a stated-adaptation survey could not be made because of the limited number of elderly respondents included in the Portland survey. Other surveys (including revealed preference, stated-preference, and stated-adaptation) should be examined to detect if, in fact, significant differences in response patterns exist between the clusters identified through this research.

(4) A number of jurisdictions other than Portland, Oregon have recently undertaken activity-based surveys. As these data become available, the application of the framework developed in this study to determine its transferability would be useful.

(5) The model developed as part of this research did not incorporate temporal and spatial attributes of individual activities. This would inherently provide more sophisticated constraining rules for the model structure. The next generation of this framework should include a scheduling algorithm (discussed in section 2.2.2) to allow a more behavioural response to policy and service options. The final use of the model should dictate whether this increased capability is worth the additional effort and complexity associated with such a modification.

(6) The approach used within the framework of the activity-based model considers the behaviour and patterns of the individual. The relationships and interactions between household members

should be more explicitly modelled so that the effects on travel behaviour can be understood. This is a particularly important aspect for the elderly given their increasing dependence on others to meet their travel needs.

(7) If the framework is to be used for the examination of policy through a stated-response survey, the respondents' choices need to be described in greater detail than what has traditionally been done. The full effects of a proposed policy on each respondent's daily activity itinerary must be known to allow the model to estimate the aggregate impact. Traditional responses like 'would make trip less often' are too ambiguous to be useful for inclusion in the model. A HATS-type survey instrument (discussed in section 2.2.2) should be used and the results applied by the developed framework.

(8) The ability of the model to produce accurate forecasts of travel demand should be explored. The ability to estimate future populations within individual lifestyle groups depends greatly on the specific variables used to delineate clusters. Obtaining forecasts for variables such as income or household structure which were used for stratification will be appreciably more difficult than for variables such as age or license holding.

Evolving cohort effects should be studied since they may contradict an assumption that fundamental travel behaviour within each category will remain consistent with base year characteristics.

(9) The final 'proof' of the modelling framework could be achieved through a retrospective analysis of policy application. If a test case could be found where stated-response surveys were executed, a policy implemented, and the net effects monitored, then the model could be applied and compared with actual results.

8.3 Final Comments

The most significant contributions of the research include the delineation of the elderly into different lifestyle groups with correspondingly varied travel behaviours, the development of a simplified activity-based travel model, and its application to test cases. An important first step has been taken toward the development of a comprehensive modelling framework that can be used to estimate the impacts of policies on specific groups of individuals. The activity-based framework not only measures the net effect of trip-making, but the impacts on individual activity participation can be gauged as well.

It is essential that planners recognize and respond to the fact that some groups can be more adversely affected by policies than the population overall. Most of the current activity-based models being developed are designed to represent the travel demands and responses for an entire MPO. These large scale models often focus on congestion and travel management for transportation networks. The framework developed through this research meets a far less ambitious need of providing a tool that allows researchers to study the travel behaviours and needs of specific subgroups of the population. The model helps to identify any adverse impacts so that some form of mitigation might be employed.

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Appendix A

Portland Study Area

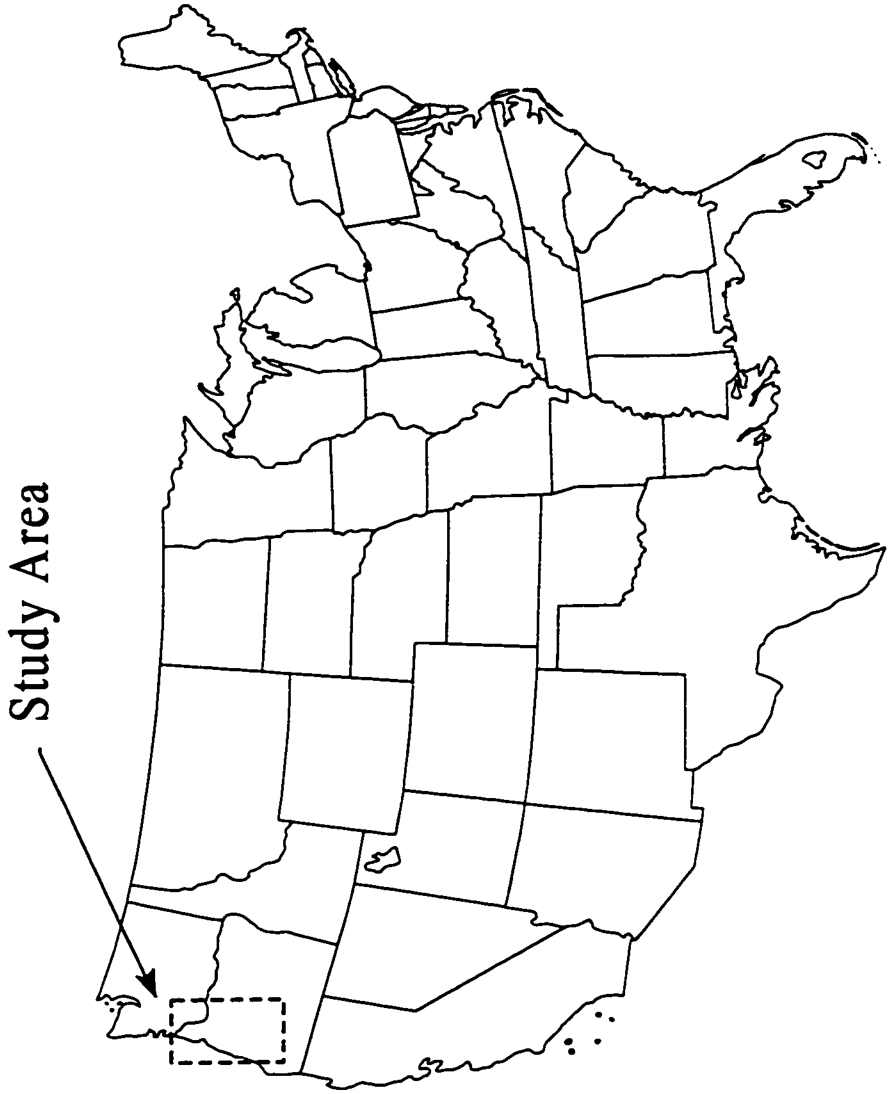

Figure A.1: Location Map for Portland, Oregon Study Area

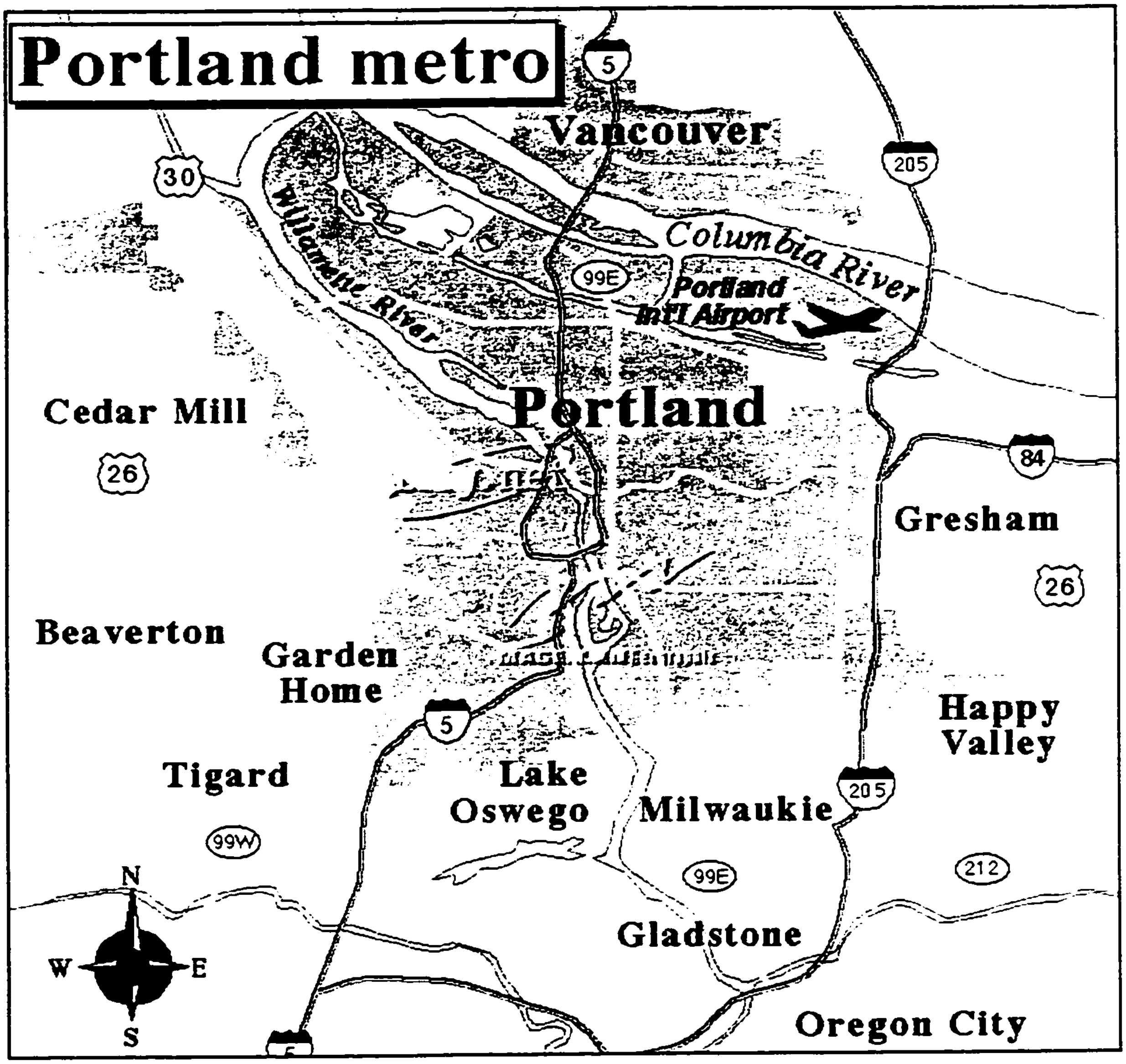

Figure A.2: Portland, Oregon and Surrounding Vicinity

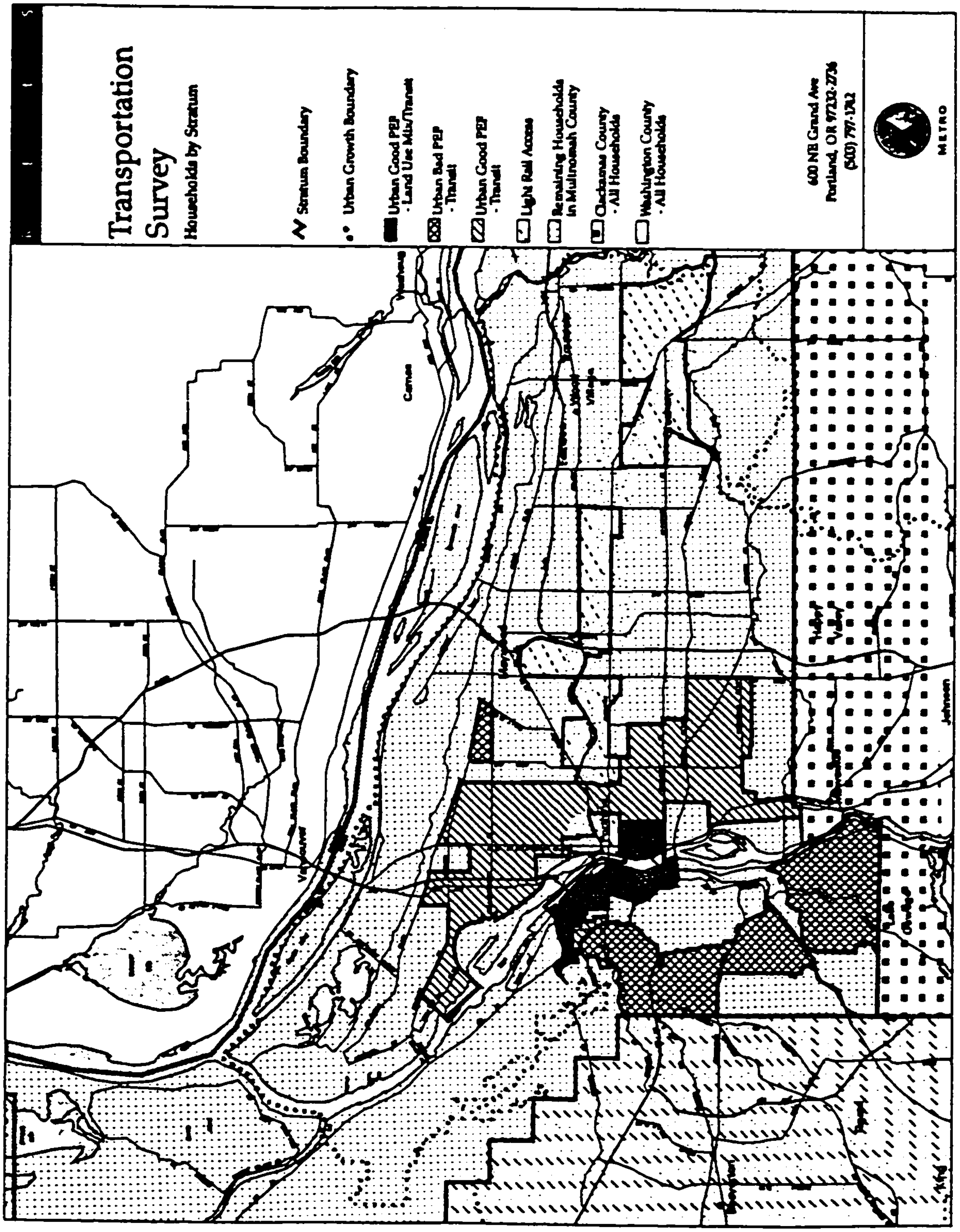

Figure A.3: Geographic Strata of Portland Study Area

Appendix B

Exemplary Activity-Based Data

Data Items Collected in the 1994 Household Activity and Travel Behavior Survey

Household Data Elements
- Address
- Activity dates
- Household size and names
- Household structure type
- Household income
- Number of phone lines
- Number of cellular or car phones
- Presence/absence of household members or visitors on activity day
- Tenure at current address
- Zip code of previous address
- Own or rent
- Number of vehicles
- Shared phone lines
- Transportation Disability

Person Data Elements
- Gender
- Race/Ethnicity
- English proficiency
- Employment status
- Age
- Household language
- Driver's license status
- Student status

If Employed:
- Occupation
- Industry
- Work at home
- Pay for parking?
- Parking cost
- Tenure at current job
- Address of primary job
- Zip code of secondary place of work
- Primary employer offers shift work or flex time?
- Primary employer offers subsidized parking or transit?
- Number of days traveled by specific modes
- Zip code of previous employer

If Student:
- Name of School
- Number of days traveled by specific modes

Activity Diary Data Elements/Questions
- What was the activity?
- Where did it take place?
- When did activity start?
- Did you have a vehicle available?
- Parking costs, if any
- How long did it take?
- Were you already there?
- How did you get there?
- Number in party
- Start/end times
- Bus trip information (e.g. route, transfer)

Vehicle Form Data Elements/Questions
- Vehicle year, make, model, type
- Year purchased
- Fuel type
- Vehicle ownership
- Purchased as replacement or add-on?
- Odometer reading on beginning of 1st day
- Odometer reading at end of 2nd day

Source: NuStats International, *Oregon and Southwest Washington Household Activity and Travel Survey*, Revealed Preference Final Report, 1995.

Summary of Data File From Portland Metro Activity-Based Data Set

The following pages present exemplary data derived from the Portland Metro data set used for cluster analyses and simulation model development. The following is a key to the variable names:

ID:
An identification number assigned to each respondent. The integer number represents the household, while the decimal portion identifies the individual. For example, ID =200009.01 is assigned to person number 01 from household 200009.

ACT1 through ACT8:
These variables are the sum of the number of <u>hours</u> the respondent engaged in each of the 8 activity classes during the two-day survey period. The 8 activity classes are delineated in Table 4.1.

MEALS through OTHER:
These variables represent the total number of <u>times</u> the respondent engaged in each of the respective activity classes during the two-day survey period.

TRAV_M through TRAV_O:
These variables represent the total number of times the respondent engaged in each of the respective activity classes <u>when travel was required</u> during the two-day survey period.

TOTACTS:
The total number of activities requiring travel during the two-day period.

TOURS:
Total number of trip tours (beginning and ending at home) during the two-day survey period.

AVGACTS:
Average number of activities per tour.

DUR:
Average travel time to access each activity.

MS.AUTO through MS.OTHR:
The proportion of all activities requiring travel by each mode including auto, walking, transit, and other.

DRVR and PAX:
Proportion of all activities requiring travel as a driver or a passenger.

Q22:
The average number of people in the auto.

RELATN:
Categorical relation to the household head.

GENDER:
Male (10 or female (2).

AGE:
Age in years (note 99 = unknown/refused).

RACE:
Categorical variable to record race.

LICNSD:
Variable to indicate whether the respondent holds a driver's license (1 =yes, 2=no).

EMPLYD:
Categorical variable indicating the employment status of the respondent.

HDCP:
Variable to indicate whether the respondent is disabled (-1 yes, 2-no).

HOMETYPE:
Categorical variable to describe type of dwelling.

HHSIZE:
Number of persons living in the same dwelling.

VEHICLES:
Number of household-owned vehicles.

INCOME:
Total household income.

HALFMILE:
Variable to indicate if the household is within ½ mile of LRT.

COP1 through COP7:
Frequency of choice of each of 7 coping options for the stated adaptation survey on road pricing.

CHOIC1 and CHOIC2:
First and second most frequently chosen travel options for an alternative routing corresponding with the stated adaptation survey on road pricing.

ID	ACT1	ACT2	ACT3	ACT4	ACT5	ACT6	ACT7	ACT8	MEALS	SUBST	HOUSE	PERS	SOCIAL	AMSE	RECTN	OTHR	TRAV_M	TRAV_SB	TRAV_H	TRAV_P
200009.01	10.67	0.00	3.13	0.00	0.50	4.50	4.33	0.00	5	0	2	0	1	2	1	0	1	0	2	0
200015.01	2.00	0.00	0.00	0.00	2.00	19.25	0.00	0.00	2	0	0	0	2	5	0	0	0	0	0	0
200020.01	1.08	0.00	14.00	1.75	0.00	8.33	0.00	0.00	2	0	4	1	0	4	0	0	0	0	1	1
200029.01	6.25	0.00	3.91	1.00	0.00	11.00	1.00	0.00	2	0	3	1	0	5	2	0	0	0	3	1
200029.02	6.50	13.33	0.22	0.00	1.66	9.50	0.00	0.00	5	5	2	0	3	4	0	0	2	3	2	0
200061.01	1.50	0.00	1.92	0.00	0.00	6.00	2.25	0.00	1	0	2	0	0	3	2	0	0	0	2	0
200061.02	1.25	0.00	4.84	0.00	0.00	5.67	0.00	0.58	2	0	4	0	0	2	0	1	1	0	2	0
200090.01	2.91	0.00	4.39	2.83	2.25	12.97	0.00	0.00	4	0	6	2	2	7	0	0	0	0	6	2
200090.02	6.25	0.00	10.66	0.00	0.00	10.60	0.00	0.00	7	0	6	0	0	6	0	0	0	0	3	0
200101.01	5.00	0.00	3.00	0.00	6.50	11.50	4.00	0.00	2	0	1	0	2	2	1	0	1	0	0	0
200102.01	1.75	17.00	0.25	0.67	2.00	4.42	8.25	0.00	2	3	1	1	1	3	2	0	0	2	1	1
200107.01	6.41	0.00	5.00	0.00	0.00	15.00	1.50	0.00	6	0	4	0	0	9	2	0	2	0	1	0
200123.01	2.50	0.00	0.00	0.00	0.00	6.00	23.50	0.00	4	0	0	0	0	4	4	0	0	0	0	0
200126.01	4.00	0.00	4.50	0.00	9.00	10.75	0.00	0.00	4	0	2	0	3	4	0	0	2	0	0	0
200137.01	1.00	9.25	2.66	1.50	0.00	11.08	0.00	0.00	1	1	3	1	0	4	0	0	1	1	3	1
200137.02	1.00	0.00	0.00	0.00	0.00	24.17	0.00	0.00	1	0	0	0	0	2	0	0	1	0	0	0
200149.01	2.00	0.00	6.83	0.00	2.50	1.50	12.25	0.00	2	0	4	0	1	1	4	0	0	0	3	0
200149.02	3.75	0.00	0.00	1.83	2.50	8.50	7.00	0.00	4	0	0	2	1	3	1	0	2	0	0	2
200153.01	4.92	0.00	10.84	2.42	7.83	6.00	0.75	1.44	4	0	8	2	8	3	1	3	3	0	3	2
200191.01	2.50	1.50	1.00	0.00	0.00	16.33	1.17	0.25	3	1	1	0	0	6	1	2	2	1	1	0
200191.02	1.75	0.00	3.51	0.00	0.00	13.92	0.00	0.25	2	0	5	0	0	7	0	2	2	0	3	0
200249.03	3.00	6.00	11.00	0.00	0.00	3.50	0.00	0.50	3	1	2	0	0	2	0	1	2	1	2	0
200251.02	1.00	0.00	10.00	0.00	0.00	1.00	3.00	0.00	2	0	4	0	0	1	1	0	0	0	0	0
200255.01	2.83	0.00	4.50	0.00	0.00	15.08	5.00	0.00	5	0	2	0	0	8	2	0	1	0	1	0
200270.01	2.00	0.00	0.75	0.91	0.00	12.09	0.00	0.00	2	0	1	1	0	4	0	0	0	0	1	1
200271.01	4.84	6.25	3.00	0.75	0.00	7.08	0.00	0.05	5	6	5	1	0	5	0	1	2	6	4	1
200286.01	3.58	0.00	18.41	1.00	0.00	4.50	0.00	0.00	4	0	11	1	0	2	0	0	0	0	5	1
200290.01	4.25	0.00	5.67	0.00	2.50	6.75	7.25	0.00	4	0	3	0	1	2	3	0	2	0	2	0
200290.02	3.00	0.00	3.50	0.00	4.00	9.23	6.25	0.00	2	0	1	0	3	5	3	0	0	0	0	0
200291.02	2.75	0.00	18.67	0.50	0.00	5.75	0.00	0.50	3	0	6	1	0	3	0	1	0	0	4	1
200299.01	2.97	0.00	3.59	0.75	0.00	11.22	8.00	0.00	3	0	8	1	0	4	3	0	3	0	8	0
200299.02	2.97	0.00	2.34	2.25	0.00	9.63	8.00	0.00	3	0	6	1	0	2	1	0	3	0	6	1
200319.01	3.00	0.00	10.17	0.00	0.50	15.50	0.00	0.00	6	0	7	0	1	5	0	0	0	0	3	0
200325.01	3.16	0.00	3.08	0.00	0.00	7.25	12.99	0.00	4	0	2	0	0	3	4	0	2	0	1	0
200330.02	5.58	0.00	3.28	0.00	2.25	6.92	0.00	1.33	5	0	4	0	1	3	0	2	3	0	3	0

ID	TRAV_SC	TRAV_AM	TRAV_R	TRAV_O	TOTACTS	TOURS	AVGACTS	DUR	MS AUTO	MS WLK	MS TRNST	MS OTHR	DRVR	PAX	Q22	RELATN	GENDR	AGE
200009.01	0	1	1	0	5	2	2.50	8.00	0.00	0.80	0.20	0.00	0.00	0.00	NA	9	2	82
200015.01	2	1	0	0	3	1	3.00	15.00	0.00	0.00	0.00	1.00	0.00	0.00	NA	9	1	82
200020.01	0	1	0	0	3	1	3.00	23.33	0.00	0.67	0.33	0.00	0.00	0.00	NA	9	1	77
200029.01	0	4	2	0	10	3	3.33	12.50	1.00	0.00	0.00	0.00	1.00	0.00	1.00	9	2	66
200029.02	2	1	0	0	10	3	3.33	13.70	1.00	0.00	0.00	0.00	1.00	0.00	1.00	1	1	66
200061.01	0	0	2	0	4	2	2.00	10.00	1.00	0.00	0.00	0.00	0.75	0.25	1.50	9	2	77
200061.02	0	0	0	1	4	2	2.00	17.50	1.00	0.00	0.00	0.00	1.00	0.00	1.50	1	1	75
200090.01	1	3	0	0	12	4	3.00	15.00	1.00	0.00	0.00	0.00	1.00	0.00	1.25	9	1	79
200090.02	0	0	0	0	3	1	3.00	7.67	1.00	0.00	0.00	0.00	0.00	1.00	2.00	1	2	78
200101.01	1	0	0	0	2	1	2.00	37.50	0.00	0.00	1.00	0.00	0.00	0.00	NA	9	1	85
200102.01	1	3	0	0	8	4	2.00	50.00	0.38	0.50	0.00	0.13	0.00	0.38	2.67	9	2	66
200107.01	0	1	1	0	5	3	1.67	22.00	0.80	0.20	0.00	0.00	0.40	0.40	2.50	9	2	74
200123.01	0	0	0	0	0	0	0.00	NA	NA	NA	NA	NA	NA	NA	NA	9	2	80
200126.01	2	0	0	0	4	2	2.00	10.00	1.00	0.00	0.00	0.00	1.00	0.00	1.00	9	1	84
200137.01	0	3	0	0	9	4	2.25	10.56	1.00	0.00	0.00	0.00	1.00	0.00	1.11	9	2	67
200137.02	0	0	0	0	1	1	1.00	5.00	1.00	0.00	0.00	0.00	0.00	1.00	2.00	1	1	71
200149.01	1	0	2	0	6	3	2.00	13.17	1.00	0.00	0.00	0.00	1.00	0.00	2.00	9	1	86
200149.02	1	0	0	0	5	2	2.50	18.00	1.00	0.00	0.00	0.00	0.00	1.00	2.80	1	2	83
200153.01	5	0	0	3	16	4	4.00	14.31	0.81	0.19	0.00	0.00	0.69	0.13	1.38	9	1	72
200191.01	0	1	1	2	8	3	2.67	44.38	0.75	0.25	0.00	0.00	0.75	0.00	1.33	9	2	68
200191.02	0	2	0	2	9	4	2.25	37.78	1.00	0.00	0.00	0.00	0.78	0.22	1.67	3	2	65
200249.03	0	2	0	1	8	3	2.67	29.38	1.00	0.00	0.00	0.00	1.00	0.00	1.25	2	1	66
200251.02	0	0	0	0	0	0	0.00	NA	NA	NA	NA	NA	NA	NA	NA	1	2	67
200255.01	0	0	0	0	2	1	2.00	15.00	1.00	0.00	0.00	0.00	1.00	0.00	1.00	9	2	84
200270.01	0	2	0	0	4	2	2.00	13.75	1.00	0.00	0.00	0.00	0.75	0.25	1.25	9	1	75
200271.01	0	0	0	1	14	2	7.00	16.93	0.86	0.14	0.00	0.00	0.86	0.00	1.17	9	2	67
200286.01	0	0	0	0	6	2	3.00	7.50	1.00	0.00	0.00	0.00	1.00	0.00	1.00	9	2	70
200290.01	1	1	3	0	9	4	2.25	26.78	0.89	0.11	0.00	0.00	0.89	0.00	1.25	9	1	79
200290.02	1	4	3	0	8	4	2.00	28.25	0.75	0.25	0.00	0.00	0.50	0.25	1.33	1	2	78
200291.02	0	1	0	1	7	3	2.33	13.57	1.00	0.00	0.00	0.00	0.29	0.71	2.14	1	1	66
200299.01	0	2	2	0	15	4	3.75	9.00	1.00	0.00	0.00	0.00	1.00	0.00	1.67	9	1	71
200299.02	0	2	1	0	13	3	4.33	9.62	1.00	0.00	0.00	0.00	0.00	1.00	2.00	1	2	70
200319.01	1	0	0	0	4	2	2.00	7.50	1.00	0.00	0.00	0.00	1.00	0.00	1.00	9	2	73
200325.01	0	0	3	0	6	3	2.00	10.00	1.00	0.00	0.00	0.00	0.00	1.00	2.00	9	2	73
200330.02	1	2	0	2	11	2	5.50	25.73	0.73	0.27	0.00	0.00	0.00	0.73	5.00	1	1	65

ID	RACE	LICNSD	EMPLYD	HDCP	HOMETYPE	HHSIZE	VEHICLES	INCOME	HALFMILE	COP1	COP2	COP3	COP4	COP5	COP6	COP7	CHOIC1	CHOIC2
200009.01	1	2	6	2	2	1	0	1	0	NA	NA	NA	NA	NA	NA	NA		
200015.01	1	2	6	1	2	1	0	14	0	NA	NA	NA	NA	NA	NA	NA		
200020.01	1	2	6	2	2	1	0	2	0	NA	NA	NA	NA	NA	NA	NA		
200029.01	1	1	4	2	1	3	3	4	0	NA	NA	NA	NA	NA	NA	NA		
200029.02	1	1	3	2	1	3	3	4	0	NA	NA	NA	NA	NA	NA	NA		
200061.01	1	1	6	2	1	2	3	14	0	NA	NA	NA	NA	NA	NA	NA		
200061.02	1	1	6	2	1	2	3	14	0	NA	NA	NA	NA	NA	NA	NA		
200090.01	1	1	6	2	1	2	1	5	0	NA	NA	NA	NA	NA	NA	NA		
200090.02	1	1	6	2	1	2	1	5	0	NA	NA	NA	NA	NA	NA	NA		
200101.01	1	2	6	1	2	1	0	2	0	NA	NA	NA	NA	NA	NA	NA		
200102.01	1	2	1	2	2	1	0	8	0	NA	NA	NA	NA	NA	NA	NA		
200107.01	1	1	6	2	1	1	1	4	0	1	6	5	0	4	0	0	B	
200123.01	1	1	6	2	1	2	2	2	0	NA	NA	NA	NA	NA	NA	NA		
200126.01	1	1	6	2	1	1	1	2	0	NA	NA	NA	NA	NA	NA	NA		
200137.01	1	1	1	2	1	2	1	9	1	NA	NA	NA	NA	NA	NA	NA		
200137.02	1	2	6	2	1	2	1	9	1	NA	NA	NA	NA	NA	NA	NA		
200149.01	1	1	6	2	1	2	1	4	0	NA	NA	NA	NA	NA	NA	NA		
200149.02	1	2	9	2	1	2	1	4	0	NA	NA	NA	NA	NA	NA	NA		
200153.01	1	1	6	2	2	1	1	7	1	NA	NA	NA	NA	NA	NA	NA		
200191.01	1	1	6	2	1	2	2	7	0	NA	NA	NA	NA	NA	NA	NA		
200191.02	1	1	6	2	1	2	2	7	0	NA	NA	NA	NA	NA	NA	NA		
200249.03	1	1	3	2	1	5	4	11	0	NA	NA	NA	NA	NA	NA	NA		
200251.02	1	1	6	2	1	2	2	14	1	NA	NA	NA	NA	NA	NA	NA		
200255.01	1	1	6	1	2	1	1	14	0	NA	NA	NA	NA	NA	NA	NA		
200270.01	1	1	6	2	2	1	1	4	0	NA	NA	NA	NA	NA	NA	NA		
200271.01	1	1	3	2	1	1	1	14	0	NA	NA	NA	NA	NA	NA	NA		
200286.01	1	1	6	2	1	1	1	2	0	2	5	5	0	5	0	0	A	B
200290.01	1	1	6	2	1	2	2	6	0	NA	NA	NA	NA	NA	NA	NA		
200290.02	1	1	6	2	1	2	2	6	0	NA	NA	NA	NA	NA	NA	NA		
200291.02	1	1	6	2	1	3	2	3	0	NA	NA	NA	NA	NA	NA	NA		
200299.01	1	1	6	2	1	2	2	6	0	0	8	0	6	5	0	0	B	D
200299.02	1	1	6	2	1	2	2	6	0	NA	NA	NA	NA	NA	NA	NA		
200319.01	1	1	6	2	1	1	1	14	0	NA	NA	NA	NA	NA	NA	NA		
200325.01	1	1	6	2	1	2	1	4	0	NA	NA	NA	NA	NA	NA	NA		
200330.02	1	1	6	2	1	2	2	9	0	NA	NA	NA	NA	NA	NA	NA		

Appendix C

GPSS/H Simulation Model

The following programming code represents the final version of the GPSS/H simulation model developed through the analyses of Chapter 6.

```
       SIMULATE
       INTEGER         &C1,&A1,&A2,&A3,&A4,&A5,&A6,&A7,&A8,&A9,&A10,&A11,&A12,_
&T1,&T2,&T3,&T4,&T5,&T6,&T7,&T8,&X,&C3,&Y,&Z,&U1,&U2,&U3,&U4,&U5,&U6,&U7,&U8,_
&V1,&V2,&V3,&V4,&V5,&V6,&V7,&V8,&M1,&M2,&M3,&M4,&M5,&M6
       REAL            &TR,&P,&C2
*
*       PhD Thesis: An Activity-Based Travel Needs Model for the Elderly
*
*       FILE= C:\GPSSH\MOD6.wpd (final version of base simulation model)
*
*       Define Functions
*
* The following function is used to assign the Xactns. into one of the 6 clusters
*
CLUST  FUNCTION         (RN99),D6       Divides into 6 clusters
0.109,1/0.402,2/0.445,3/0.567,4/0.946,5/1,6
* Above represents 10.9% in Cluster 1, 29.3% in Cluster 2, 4.3% in Cluster 3, etc.
* Cluster 1-6 are: Wrkrs, Mob Wdws, Grn Flts, Mob Imprd, Aflu M, Disbl Drvrs
*
* The following functions return the number of activities per day for each
* of the six lifestyle clusters:
*
DAY1   FUNCTION         (RN1),D11       RETURNS THE # OF ACTS. IN A DAY for CLUSTER1
0.032,2/0.088,3/0.160,4/0.296,5/0.484,6/0.628,7/0.732,8/0.808,9/0.872,10/0.928,11/1,12
DAY2   FUNCTION         (RN2),D11       # ACTIVITIES PER DAY FOR CLUSTER 2
0.025,2/0.055,3/0.093,4/0.180,5/0.353,6/0.493,7/0.626,8/0.776,9/0.855,10/0.914,11/1,12
DAY3   FUNCTION         (RN3),D11       # ACTIVITIES PER DAY FOR CLUSTER 3
0.090,2/0.150,3/0.250,4/0.360,5/0.570,6/0.730,7/0.800,8/0.900,9/0.960,10/0.990,11/1,12
DAY4   FUNCTION         (RN4),D11       # ACTIVITIES PER DAY FOR CLUSTER 4
0.025,2/0.043,3/0.106,4/0.252,5/0.472,6/0.589,7/0.723,8/0.869,9/0.926,10/0.965,11/1,12

DAY5   FUNCTION         (RN5),D11       # ACTIVITIES PER DAY FOR CLUSTER 5
0.032,2/0.060,3/0.122,4/0.197,5/0.380,6/0.529,7/0.675,8/0.812,9/0.896,10/0.950,11/1,12
DAY6   FUNCTION         (RN6),D11       # ACTIVITIES PER DAY FOR CLUSTER 6
0.066,2/0.074,3/0.115,4/0.246,5/0.443,6/0.582,7/0.697,8/0.861,9/0.902,10/0.926,11/1,12
*
* The following functions return the number of travel activities per day depending
* on the cluster
*
TRV1   FUNCTION         (RN40),D11      #TRAVL ACTS/DAY CLUSTER 1
0.09,0/0.112,0.1/0.152,0.2/0.204,0.3/0.349,0.4/0.421,0.5/0.558,0.6/0.695,0.7/_
0.811,0.8/0.871,0.9/1.0,1.0
TRV2   FUNCTION         (RN41),D11      #TRAVL ACTS/DAY CLUSTER 2
0.239,0/0.245,0.1/0.308,0.2/0.411,0.3/0.562,0.4/0.640,0.5/0.761,0.6/0.840,0.7/_
0.906,0.8/0.948,0.9/1.0,1.0
TRV3   FUNCTION         (RN42),D11      #TRAVL ACTS/DAY CLUSTER 3
0.570,0/0.571,0.1/0.620,0.2/0.730,0.31/0.780,0.4/0.870,0.5/0.890,0.6/0.940,0.7/_
0.970,0.8/0.990,0.9/1.0,1.0
TRV4   FUNCTION         (RN43),D11      #TRAVL ACTS/DAY CLUSTER 4
0.454,0/0.458,0.1/0.519,0.2/0.624,0.3/0.649,0.4/0.785,0.5/0.860,0.6/0.946,0.7/_
0.996,0.8/0.997,0.9/1.0,1.0
TRV5   FUNCTION         (RN44),D11      #TRAVL ACTS/DAY CLUSTER 5
0.215,0/0.251,0.1/0.292,0.2/0.409,0.3/0.455,0.4/0.620,0.5/0.766,0.6/0.818,0.7/_
0.872,0.8/0.951,0.9/1.0,1.0
```

```
TRV6    FUNCTION          (RN45),D11       #TRAVL ACTS/DAY CLUSTER 6
0.410,0/0.411,0.1/0.470,0.2/0.622,0.3/0.665,0.4/0.750,0.5/0.833,0.6/0.858,0.7/_
0.900,0.8/0.950,0.9/1.0,1.0
*
* THE FOLLOWING IS A ROUNDING FUNCTION
*
RND     FUNCTION          &C2,D13          A FUNCTION TO ROUND OFF NUMBERS
0.500,0/0.950,1/2.750,2/3.500,3/4.500,4/5.500,5/6.500,6/7.500,7/8.500,8/9.500,9/_
10.500,10/11.500,11/13.000,12
*
*
* THE FOLLOWING FUNCTIONS DEFINE THE PROBABILITIES OF ENGAGING IN EACH OF THE
* EIGHT ACTIVITY CLASSES GIVEN THE CLUSTER NO. AND THE TOTAL ACTIVITIES PER DAY
*
* eg. ACT104 is for cluster 1 with 0 to 4 activities per day
*
ACT104 FUNCTION          (RN7),D16        PROBS. FOR 8 ACTS./CLUTR=1\ACTS/DAY=0-4
0.12,1/0.242,11/0.265,2/0.507,12/0.563,3/0.661,13/0.6611,4/0.6612,14/
0.6613,5/0.672,15/0.869,6/0.957,16/0.978,7/0.989,17/0.9891,8/1,18
ACT156 FUNCTION          (RN8),D16        PROBS. FOR 8 ACTS./CLUTR=1\ACTS/DAY=5,6
0.145,1/0.26,11/0.275,2/0.412,12/0.472,3/0.594,13/0.597,4/0.602,14/
0.612,5/0.652,15/0.813,6/0.90,16/0.96,7/0.965,17/0.9651,8/1,18
ACT178 FUNCTION          (RN9),D16        PROBS. FOR 8 ACTS./CLUTR=1\ACTS/DAY=7,8
0.169,1/0.252,11/0.322,2/0.43,12/0.477,3/0.593,13/0.5931,4/0.604,14/
0.619,5/0.657,15/0.785,6/0.878,16/0.916,7/0.962,17/0.964,8/1,18
ACT19P FUNCTION          (RN10),D16       PROBS. FOR 8 ACTS./CLUTR=1\ACTS/DAY=9+
0.156,1/0.246,11/0.28,2/0.392,12/0.465,3/0.606,13/0.6061,4/0.622,14/
0.639,5/0.673,15/0.834,6/0.876,16/0.899,7/0.945,17/0.9451,8/1,18
*
* cluster 2
*
ACT204 FUNCTION          (RN12),D16         PROBS. FOR 8 ACTS./CLUTR=2 \ACTS/DAY=0-4
0.127,1/0.207,11/0.2071,2/0.2072,12/0.304,3/0.423,13/0.4231,4/0.44,14/
0.457,5/0.521,15/0.769,6/0.856,16/0.928,7/0.992,17/0.9921,8/1,18
ACT256 FUNCTION          (RN13),D16         PROBS. FOR 8 ACTS./CLUTR=2 \ACTS/DAY=5-6
0.207,1/0.286,11/0.289,2/0.295,12/0.407,3/0.526,13/0.5261,4/0.545,14/
0.574,5/0.622,15/0.802,6/0.879,16/0.916,7/0.977,17/0.9771,8/1,18
ACT278 FUNCTION          (RN14),D16         PROBS. FOR 8 ACTS./CLUTR=2 \ACTS/DAY=7-8
0.196,1/0.275,11/0.276,2/0.283,12/0.391,3/0.533,13/0.535,4/0.553,14/
0.579,5/0.62,15/0.833,6/0.90,16/0.931,7/0.963,17/0.9631,8/1,18
ACT291 FUNCTION          (RN15),D16         PROBS. FOR 8 ACTS./CLUTR=2 \ACTS/DAY=9,10
0.20,1/0.269,11/0.272,2/0.275,12/0.407,3/0.543,13/0.545,4/0.562,14/
0.603,5/0.644,15/0.862,6/0.908,16/0.929,7/0.969,17/0.9691,8/1,18
ACT211 FUNCTION          (RN16),D16         PROBS. FOR 8 ACTS./CLUTR=2 \ACTS/DAY=11+
0.183,1/0.238,11/0.24,2/0.244,12/0.372,3/0.506,13/0.511,4/0.528,14/
0.565,5/0.615,15/0.842,6/0.895,16/0.933,7/0.962,17/0.963,8/1,18
*
* cluster 3
*
ACT305 FUNCTION          (RN17),D16         PROBS. FOR 8 ACTS./CLUTR=3 \ACTS/DAY=0-5
0.225,1/0.265,11/0.2651,2/0.275,12/0.372,3/0.441,13/0.46,4/0.50,14/
0.5001,5/0.519,15/0.735,6/0.754,16/0.939,7/0.979,17/0.9791,8/1,18
ACT367 FUNCTION          (RN18),D16         PROBS. FOR 8 ACTS./CLUTR=3 \ACTS/DAY=6,7
0.295,1/0.338,11/0.346,2/0.359,12/0.461,3/0.529,13/0.5291,4/0.5292,14/
0.541,5/0.567,15/0.898,6/0.915,16/0.962,7/0.983,17/0.9831,8/1,18
ACT38P FUNCTION          (RN19),D16         PROBS. FOR 8 ACTS./CLUTR=3 \ACTS/DAY=8+
0.258,1/0.298,11/0.2981,2/0.2982,12/0.41,3/0.479,13/0.4791,4/0.497,14/
0.511,5/0.522,15/0.824,6/0.867,16/0.917,7/0.939,17/0.9391,8/1,18
*
```

```
* cluster 4
*
ACT404 FUNCTION          (RN20),D16       PROBS. FOR 8 ACTS./CLUTR=4  ACTS/DAY=0-4
0.276,1/0.328,11/0.3281,2/0.362,12/0.414,3/0.448,13/0.4481,4/0.4482,14/
0.50,5/0.517,15/0.896,6/0.948,16/0.9997,7/0.9998,17/0.9999,8/1,18
ACT456 FUNCTION          (RN21),D16       PROBS. FOR 8 ACTS./CLUTR=4 \ACTS/DAY=5,6
0.287,1/0.337,11/0.34,2/0.344,12/0.416,3/0.472,13/0.4721,4/0.491,14/
0.517,5/0.563,15/0.822,6/0.88,16/0.974,7/0.996,17/0.9961,8/1,18
ACT478 FUNCTION          (RN22),D16       PROBS. FOR 8 ACTS./CLUTR=4 \ACTS/DAY=7,8
0.261,1/0.306,11/0.309,2/0.313,12/0.40,3/0.509,13/0.513,4/0.522,14/
0.57,5/0.589,15/0.86,6/0.891,16/0.96,7/0.989,17/0.9891,8/1,18
ACT49P FUNCTION          (RN23),D16       PROBS. FOR 8 ACTS./CLUTR=4 \ACTS/DAY=9+
0.245,1/0.276,11/0.282,2/0.285,12/0.393,3/0.468,13/0.471,4/0.483,14/
0.54,5/0.561,15/0.839,6/0.886,16/0.96,7/0.984,17/0.987,8/1,18
*
* cluster 5
*
ACT504 FUNCTION          (RN24),D16       PROBS. FOR 8 ACTS./CLUTR=5 \ACTS/DAY=0-4
0.104,1/0.186,11/0.189,2/0.204,12/0.261,3/0.378,13/0.388,4/0.417,14/
0.451,5/0.495,15/0.668,6/0.808,16/0.852,7/0.943,17/0.9431,8/1,18
ACT556 FUNCTION          (RN25),D16       PROBS. FOR 8 ACTS./CLUTR=5 \ACTS/DAY=5,6
0.191,1/0.271,11/0.276,2/0.28,12/0.395,3/0.507,13/0.509,4/0.524,14/
0.54,5/0.585,15/0.798,6/0.889,16/0.92,7/0.98,17/0.9801,8/1,18
ACT578 FUNCTION          (RN26),D16       PROBS. FOR 8 ACTS./CLUTR=5  ACTS/DAY=7,8
0.199,1/0.272,11/0.2721,2/0.275,12/0.375,3/0.506,13/0.5061,4/0.52,14/
0.545,5/0.59,15/0.812,6/0.883,16/0.927,7/0.967,17/0.9671,8/1,18
ACT591 FUNCTION          (RN27),D16       PROBS. FOR 8 ACTS./CLUTR=5  ACTS/DAY=9,10
0.193,1/0.266,11/0.267,2/0.2671,12/0.382,3/0.526,13/0.527,4/0.549,14/
0.582,5/0.618,15/0.829,6/0.886,16/0.923,7/0.969,17/0.9691,8/1,18
ACT511 FUNCTION          (RN28),D16       PROBS. FOR 8 ACTS./CLUTR=5  ACTS/DAY=11+
0.180,1/0.233,11/0.234,2/0.241,12/0.358,3/0.488,13/0.4881,4/0.51,14/
0.552,5/0.587,15/0.865,6/0.907,16/0.951,7/0.984,17/0.9841,8/1,18
*
* cluster 6
*
ACT605 FUNCTION          (RN29),D16       PROBS. FOR 8 ACTS./CLUTR=6  ACTS/DAY=0-5
0.168,1/0.277,11/0.2771,2/0.2772,12/0.356,3/0.455,13/0.4551,4/0.495,14/
0.514,5/0.5141,15/0.713,6/0.812,16/0.93,7/0.97,17/0.971,8/1,18
ACT668 FUNCTION          (RN30),D16       PROBS. FOR 8 ACTS./CLUTR=6 \ACTS/DAY=6-8
0.247,1/0.31,11/0.3101,2/0.3102,12/0.419,3/0.514,13/0.517,4/0.542,14/
0.575,5/0.605,15/0.851,6/0.889,16/0.958,7/0.979,17/0.9791,8/1,18
ACT69P FUNCTION          (RN31),D16       PROBS. FOR 8 ACTS./CLUTR=6 \ACTS/DAY=9+
0.21,1/0.26,11/0.2601,2/0.263,12/0.374,3/0.515,13/0.5151,4/0.523,14/
0.547,5/0.589,15/0.873,6/0.918,16/0.976,7/0.987,17/0.9871,8/1,18
*
* The following functions define the mode splits for each cluster
* personal auto =1, non-pers. auto =11, walk=2, transit=3, other=4
*
MOD1   FUNCTION          (RN50),D5       Mode splits for cluster 1 w/o recreation
0.925,1/0.949,11/0.985,2/0.999,3/1,4
MOD1R  FUNCTION          (RN51),D4     If actvty=recrtn, walk prob=26.9%
0.701,1/0.720,11/0.989,2/1,3
MOD2   FUNCTION          (RN52),D5       Mode splits for cluster 2 w/o recreation
0.827,1/0.888,11/0.967,2/0.989,3/1,4
MOD2R  FUNCTION          (RN53),D5     If actvty=recrtn, walk prob=21.5%
0.705,1/0.757,11/0.972,2/0.991,3/1,4
MOD3   FUNCTION          (RN54),D5       Mode splits for cluster 3 w/o rcretn
0.720,1/0.768,11/0.928,2/0.945,3/1,4
MOD3R  FUNCTION          (RN55),D5     If actvty=recrtn, walk prob=13.3%
0.748,1/0.792,11/0.925,2/0.942,3/1,4
```

```
MOD4    FUNCTION          (RN56),D5      Mode splits for cluster 4 w/o recretn
0.314,1/0.558,11/0.802,2/0.967,3/1,4
MOD4R   FUNCTION          (RN57),D5     If actvty=recrtn, walk prob=30.6%
0.288,1/0.512,11/0.818,2/0.969,3/1,4
MOD5    FUNCTION          (RN58),D5      Mode splits for cluster 5 w/o recreation
0.902,1/0.927,11/0.972,2/0.989,3/1,4
MOD5R   FUNCTION          (RN59),D5     If actvty=recrtn, walk prob=24.2%
0.716,1/0.736,11/0.978,2/0.992,3/1,4
MOD6    FUNCTION          (RN60),D5      Mode splits for cluster 6 w/o recreation
0.875,1/0.939,11/0.987,2/0.993,3/1,4
MOD6R   FUNCTION          (RN61),D5     If actvty=recrtn, walk prob=25.0%
0.690,1/0.740,11/0.990,2/0.995,3/1,4
*
*
*
*cols. 8                  25
        GENERATE          10,,,,,13PB
        ADVANCE           1
        ASSIGN            CNO,FN(CLUST),PB CLUSTER MEMBERSHIP ASSIGNED TO XACTN
        BLET              &A1=0
        BLET              &A2=0
        BLET              &A3=0
        BLET              &A4=0
        BLET              &A5=0
        BLET              &A6=0
        BLET              &A7=0
        BLET              &A8=0
        BLET              &A9=0
        BLET              &A10=0
        BLET              &A11=0
        BLET              &A12=0
*CLUSTER 1
        TEST E            PB(CNO),1,CLU2    IF IN CLUSTER 1 CONT., OTHERWISE GO2 CLU2
        BLET              &C1=FN(DAY1)      THE # OF ACTS./DAY FOR CLUSTER 1
        BLET              &P=FN(TRV1)       RETURNS THE % OF ACTS WHICH NEED TRAVEL
NEXT4   TEST LE           &C1,4,NEXT5       IF 0-4 ACTS/DAT CONTINUE, OTHERWISE GO2 NEXT5
        BLET              &A1=FN(ACT104)    RETURN ACTIVITY 1 FROM FUNCTION
        BLET              &A2=FN(ACT104)    RETURN ACTIVITY 2 FROM FUNCTION
        TEST NE           &C1,2,DONE        IF NOT 2 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET              &A3=FN(ACT104)    RETURN ACTIVITY 3 FROM FUNCTION
        TEST NE           &C1,3,DONE        IF NOT 3 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET              &A4=FN(ACT104)    RETURN ACTIVITY 4 FROM FUNCTION
        TRANSFER          ,DONE
NEXT5   TEST LE           &C1,6,NEXT7       IF 5,6 ACTS/DAY CONT., OTHERWISE GO2 NEXT7
        BLET              &A1=FN(ACT156)    RETURN ACTIVITY 1 FROM FUNCTION
        BLET              &A2=FN(ACT156)    RETURN ACTIVITY 2 FROM FUNCTION
        BLET              &A3=FN(ACT156)    RETURN ACTIVITY 3 FROM FUNCTION
        BLET              &A4=FN(ACT156)    RETURN ACTIVITY 4 FROM FUNCTION
        BLET              &A5=FN(ACT156)    RETURN ACTIVITY 5 FROM FUNCTION
        TEST NE           &C1,5,DONE        IF NOT 5 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET              &A6=FN(ACT156)    RETURN ACTIVITY 6 FROM FUNCTION
        TRANSFER          ,DONE
NEXT7   TEST LE           &C1,8,NEXT9       IF 7,8 ACTS/DAY CONTINUE, OTHERWISE GO2 NEXT9
        BLET              &A1=FN(ACT178)    RETURN ACTIVITY 1 FROM FUNCTION
        BLET              &A2=FN(ACT178)    RETURN ACTIVITY 2 FROM FUNCTION
        BLET              &A3=FN(ACT178)    RETURN ACTIVITY 3 FROM FUNCTION
        BLET              &A4=FN(ACT178)    RETURN ACTIVITY 4 FROM FUNCTION
        BLET              &A5=FN(ACT178)    RETURN ACTIVITY 5 FROM FUNCTION
        BLET              &A6=FN(ACT178)    RETURN ACTIVITY 6 FROM FUNCTION
        BLET              &A7=FN(ACT178)    RETURN ACTIVITY 7 FROM FUNCTION
```

```
        TEST NE          &C1,7,DONE        IF NOT 7 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET             &A8=FN(ACT178)    RETURN ACTIVITY 8 FROM FUNCTION
        TRANSFER         ,DONE
NEXT9   TEST LE          &C1,12,DONE       IF 9-12 ACTS/DAY CONT., OTHERWISE GO2 DONE
        BLET             &A1=FN(ACT19P)    RETURN ACTIVITY 1 FROM FUNCTION
        BLET             &A2=FN(ACT19P)    RETURN ACTIVITY 2 FROM FUNCTION
        BLET             &A3=FN(ACT19P)    RETURN ACTIVITY 3 FROM FUNCTION
        BLET             &A4=FN(ACT19P)    RETURN ACTIVITY 4 FROM FUNCTION
        BLET             &A5=FN(ACT19P)    RETURN ACTIVITY 5 FROM FUNCTION
        BLET             &A6=FN(ACT19P)    RETURN ACTIVITY 6 FROM FUNCTION
        BLET             &A7=FN(ACT19P)    RETURN ACTIVITY 7 FROM FUNCTION
        BLET             &A8=FN(ACT19P)    RETURN ACTIVITY 8 FROM FUNCTION
        BLET             &A9=FN(ACT19P)    RETURN ACTIVITY 9 FROM FUNCTION
        TEST NE          &C1,9,DONE        IF NOT 9 ACTS/DAY CONT, OTHERWISE GO2 DONE
        BLET             &A10=FN(ACT19P)   RETURN ACTIVITY 10 FROM FUNCTION
        TEST NE          &C1,10,DONE       IF NOT 10 ACTS/DAY CONT, OTHERWISE GO2 DONE
        BLET             &A11=FN(ACT19P)   RETURN ACTIVITY 11 FROM FUNCTION
        TEST NE          &C1,11,DONE       IF NOT 11 ACTS/DAY CONT., OTHERWISE GO2 DONE
        BLET             &A12=FN(ACT19P)   RETURN ACTIVITY 12 FROM FUNCTION
        TRANSFER         ,DONE
*
*CLUSTER 2
*
CLU2    TEST E           PB(CNO),2,CLU3    IF IN CLUSTER 2 CONT., OTHERWISE GO2 CLU3
        BLET             &C1=FN(DAY2)      THE # OF ACTS./DAY FOR CLUSTER 2
        BLET             &P=FN(TRV2)       ASSIGNS THE % OF ACTS WHICH REQUIRE TRAVEL
NXT24   TEST LE          &C1,4,NXT25       IF 2-4 ACTS/DAT CONTINUE, OTHERWISE GO2 NXT25
        BLET             &A1=FN(ACT204)    RETURN ACTIVITY 1 FROM FUNCTION
        BLET             &A2=FN(ACT204)    RETURN ACTIVITY 2 FROM FUNCTION
        TEST NE          &C1,2,DONE        IF NOT 2 ACTS/DAY CONT., OTHERWISE GO2 DONE
        BLET             &A3=FN(ACT204)    RETURN ACTIVITY 3 FROM FUNCTION
        TEST NE          &C1,3,DONE        IF NOT 3 ACTS/DAY CONT, OTHERWISE GO2 DONE
        BLET             &A4=FN(ACT104)    RETURN ACTIVITY 4 FROM FUNCTION
        TRANSFER         ,DONE
NXT25   TEST LE          &C1,6,NXT27       IF 5,6 ACTS/DAY CONT., OTHERWISE GO2 NXT27
        BLET             &A1=FN(ACT256)    RETURN ACTIVITY 1 FROM FUNCTION
        BLET             &A2=FN(ACT256)    RETURN ACTIVITY 2 FROM FUNCTION
        BLET             &A3=FN(ACT256)    RETURN ACTIVITY 3 FROM FUNCTION
        BLET             &A4=FN(ACT256)    RETURN ACTIVITY 4 FROM FUNCTION
        BLET             &A5=FN(ACT256)    RETURN ACTIVITY 5 FROM FUNCTION
        TEST NE          &C1,5,DONE        IF 6 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET             &A6=FN(ACT256)    RETURN ACTIVITY 6 FROM FUNCTION
        TRANSFER         ,DONE
NXT27   TEST LE          &C1,8,NXT29       IF 7,8 ACTS/DAY CONT, OTHERWISE GO2 NXT29
        BLET             &A1=FN(ACT278)    RETURN ACTIVITY 1 FROM FUNCTION
        BLET             &A2=FN(ACT278)    RETURN ACTIVITY 2 FROM FUNCTION
        BLET             &A3=FN(ACT278)    RETURN ACTIVITY 3 FROM FUNCTION
        BLET             &A4=FN(ACT278)    RETURN ACTIVITY 4 FROM FUNCTION
        BLET             &A5=FN(ACT278)    RETURN ACTIVITY 5 FROM FUNCTION
        BLET             &A6=FN(ACT278)    RETURN ACTIVITY 6 FROM FUNCTION
        BLET             &A7=FN(ACT278)    RETURN ACTIVITY 7 FROM FUNCTION
        TEST NE          &C1,7,DONE        IF 8 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET             &A8=FN(ACT278)    RETURN ACTIVITY 8 FROM FUNCTION
        TRANSFER         ,DONE
NXT29   TEST LE          &C1,10,NXT211     IF 9,10 ACTS/DAY CONT, OTHERWISE GO2 NXT211
        BLET             &A1=FN(ACT291)    RETURN ACTIVITY 1 FROM FUNCTION
        BLET             &A2=FN(ACT291)    RETURN ACTIVITY 2 FROM FUNCTION
        BLET             &A3=FN(ACT291)    RETURN ACTIVITY 3 FROM FUNCTION
        BLET             &A4=FN(ACT291)    RETURN ACTIVITY 4 FROM FUNCTION
        BLET             &A5=FN(ACT291)    RETURN ACTIVITY 5 FROM FUNCTION
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        BLET          &A6=FN(ACT291)     RETURN ACTIVITY 6 FROM FUNCTION
        BLET          &A7=FN(ACT291)     RETURN ACTIVITY 7 FROM FUNCTION
        BLET          &A8=FN(ACT291)     RETURN ACTIVITY 8 FROM FUNCTION
        BLET          &A9=FN(ACT291)     RETURN ACTIVITY 9 FROM FUNCTION
        TEST NE       &C1,9,DONE         IF 10 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET          &A10=FN(ACT291)    RETURN ACTIVITY 10 FROM FUNCTION
        TRANSFER      ,DONE
NXT211  TEST LE       &C1,12,DONE        IF 11,12 ACTS/DAY CONT, OTHERWISE GO2 DONE
        BLET          &A1=FN(ACT211)     RETURN ACTIVITY 1 FROM FUNCTION
        BLET          &A2=FN(ACT211)     RETURN ACTIVITY 2 FROM FUNCTION
        BLET          &A3=FN(ACT211)     RETURN ACTIVITY 3 FROM FUNCTION
        BLET          &A4=FN(ACT211)     RETURN ACTIVITY 4 FROM FUNCTION
        BLET          &A5=FN(ACT211)     RETURN ACTIVITY 5 FROM FUNCTION
        BLET          &A6=FN(ACT211)     RETURN ACTIVITY 6 FROM FUNCTION
        BLET          &A7=FN(ACT211)     RETURN ACTIVITY 7 FROM FUNCTION
        BLET          &A8=FN(ACT211)     RETURN ACTIVITY 8 FROM FUNCTION
        BLET          &A9=FN(ACT211)     RETURN ACTIVITY 9 FROM FUNCTION
        BLET          &A10=FN(ACT211)    RETURN ACTIVITY 10 FROM FUNCTION
        BLET          &A11=FN(ACT211)    RETURN ACTIVITY 11 FROM FUNCTION
        TEST NE       &C1,11,DONE        IF 12 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET          &A12=FN(ACT211)    RETURN ACTIVITY 12 FROM FUNCTION
        TRANSFER      ,DONE
*
* Cluster 3
*
CLU3    TEST E        PB(CNO),3,CLU4     IF IN CLUSTER 3 CONT., OTHERWISE GO2 CLU4
        BLET          &C1=FN(DAY3)       THE # OF ACTS./DAT FOR CLUSTER 3
        BLET          &P=FN(TRV3)        RETURNS THE % OF ACTS. WHICH REQUIRE TRAVEL
NXT34   TEST LE       &C1,5,NXT36        IF 2-5 ACTS/DAT CONT., OTHERWISE GO2 NXT36
        BLET          &A1=FN(ACT305)     RETURN ACTIVITY 1 FROM FUNCTION
        BLET          &A2=FN(ACT305)     RETURN ACTIVITY 2 FROM FUNCTION
        TEST NE       &C1,2,DONE         IF 3,4,5 ACTS/DAY CONT., OTHERWISE GO2 DONE
        BLET          &A3=FN(ACT305)     RETURN ACTIVITY 3 FROM FUNCTION
        TEST NE       &C1,3,DONE         IF 4,5 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET          &A4=FN(ACT305)     RETURN ACTIVITY 4 FROM FUNCTION
        TEST NE       &C1,4,DONE         IF 5 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET          &A5=FN(ACT305)     RETURN ACTIVITY 5 FROM FUNCTION
        TRANSFER      ,DONE
NXT36   TEST LE       &C1,7,NXT38        IF 6,7 ACTS/DAY CONT., OTHERWISE GO2 NXT38
        BLET          &A1=FN(ACT367)     RETURN ACTIVITY 1 FROM FUNCTION
        BLET          &A2=FN(ACT367)     RETURN ACTIVITY 2 FROM FUNCTION
        BLET          &A3=FN(ACT367)     RETURN ACTIVITY 3 FROM FUNCTION
        BLET          &A4=FN(ACT367)     RETURN ACTIVITY 4 FROM FUNCTION
        BLET          &A5=FN(ACT367)     RETURN ACTIVITY 5 FROM FUNCTION
        BLET          &A6=FN(ACT367)     RETURN ACTIVITY 6 FROM FUNCTION
        TEST NE       &C1,6,DONE         IF 7 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET          &A7=FN(ACT367)     RETURN ACTIVITY 7 FROM FUNCTION
        TRANSFER      ,DONE
NXT38   TEST LE       &C1,12,DONE        IF 8-12 ACTS/DAY CONT, OTHERWISE GO2 DONE
        BLET          &A1=FN(ACT38P)     RETURN ACTIVITY 1 FROM FUNCTION
        BLET          &A2=FN(ACT38P)     RETURN ACTIVITY 2 FROM FUNCTION
        BLET          &A3=FN(ACT38P)     RETURN ACTIVITY 3 FROM FUNCTION
        BLET          &A4=FN(ACT38P)     RETURN ACTIVITY 4 FROM FUNCTION
        BLET          &A5=FN(ACT38P)     RETURN ACTIVITY 5 FROM FUNCTION
        BLET          &A6=FN(ACT38P)     RETURN ACTIVITY 6 FROM FUNCTION
        BLET          &A7=FN(ACT38P)     RETURN ACTIVITY 7 FROM FUNCTION
        BLET          &A8=FN(ACT38P)     RETURN ACTIVITY 8 FROM FUNCTION
        TEST NE       &C1,8,DONE         IF 9-12 ACTS/DAY CONT, OTHERWISE GO2 DONE
        BLET          &A9=FN(ACT38P)     RETURN ACTIVITY 9 FROM FUNCTION
        TEST NE       &C1,9,DONE         IF 10-12 ACTS/DAY CONT, OTHERWISE GO2 DONE
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        BLET          &A10=FN(ACT38P)  RETURN ACTIVITY 10 FROM FUNCTION
        TEST NE       &C1,10,DONE      IF 11,12 ACTS/DAY CONT, OTHERWISE GO2 DONE
        BLET          &A11=FN(ACT38P)  RETURN ACTIVITY 11 FROM FUNCTION
        TEST NE       &C1,11,DONE      IF 12 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET          &A12=FN(ACT38P)  RETURN ACTIVITY 12 FROM FUNCTION
        TRANSFER      ,DONE
*
*  Cluster 4
*
CLU4    TEST E        PB(CNO),4,CLU5   IF IN CLUSTER 4 CONT., OTHERWISE GO2 CLU5
        BLET          &C1=FN(DAY4)     THE # OF ACTS./DAT FOR CLUSTER 4
        BLET          &P=FN(TRV4)      RETURNS %ACTS WHICH NEED TRAVEL
NXT44   TEST LE       &C1,4,NXT45      IF 2-4 ACTS/DAT CONT., OTHERWISE GO2 NXT45
        BLET          &A1=FN(ACT404)   RETURN ACTIVITY 1 FROM FUNCTION
        BLET          &A2=FN(ACT404)   RETURN ACTIVITY 2 FROM FUNCTION
        TEST NE       &C1,2,DONE       IF 3,4 ACTS/DAY CONT., OTHERWISE GO2 DONE
        BLET          &A3=FN(ACT404)   RETURN ACTIVITY 3 FROM FUNCTION
        TEST NE       &C1,3,DONE       IF 4 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET          &A4=FN(ACT404)   RETURN ACTIVITY 4 FROM FUNCTION
        TRANSFER      ,DONE
NXT45   TEST LE       &C1,6,NXT47      IF 5,6 ACTS/DAY CONT, OTHERWISE GO2 NXT47
        BLET          &A1=FN(ACT456)   RETURN ACTIVITY 1 FROM FUNCTION
        BLET          &A2=FN(ACT456)   RETURN ACTIVITY 2 FROM FUNCTION
        BLET          &A3=FN(ACT456)   RETURN ACTIVITY 3 FROM FUNCTION
        BLET          &A4=FN(ACT456)   RETURN ACTIVITY 4 FROM FUNCTION
        BLET          &A5=FN(ACT456)   RETURN ACTIVITY 5 FROM FUNCTION
        TEST NE       &C1,5,DONE       IF 6 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET          &A6=FN(ACT456)   RETURN ACTIVITY 6 FROM FUNCTION
        TRANSFER      ,DONE
NXT47   TEST LE       &C1,8,NXT49      IF 7,8 ACTS/DAY CONT., OTHERWISE GO2 NXT49
        BLET          &A1=FN(ACT478)   RETURN ACTIVITY 1 FROM FUNCTION
        BLET          &A2=FN(ACT478)   RETURN ACTIVITY 2 FROM FUNCTION
        BLET          &A3=FN(ACT478)   RETURN ACTIVITY 3 FROM FUNCTION
        BLET          &A4=FN(ACT478)   RETURN ACTIVITY 4 FROM FUNCTION
        BLET          &A5=FN(ACT478)   RETURN ACTIVITY 5 FROM FUNCTION
        BLET          &A6=FN(ACT478)   RETURN ACTIVITY 6 FROM FUNCTION
        BLET          &A7=FN(ACT478)   RETURN ACTIVITY 7 FROM FUNCTION
        TEST NE       &C1,7,DONE       IF 8 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET          &A8=FN(ACT478)   RETURN ACTIVITY 8 FROM FUNCTION
        TRANSFER      ,DONE
NXT49   TEST LE       &C1,12,DONE      IF 9-12 ACTS/DAY CONT., OTHERWISE GO2 DONE
        BLET          &A1=FN(ACT49P)   RETURN ACTIVITY 1 FROM FUNCTION
        BLET          &A2=FN(ACT49P)   RETURN ACTIVITY 2 FROM FUNCTION
        BLET          &A3=FN(ACT49P)   RETURN ACTIVITY 3 FROM FUNCTION
        BLET          &A4=FN(ACT49P)   RETURN ACTIVITY 4 FROM FUNCTION
        BLET          &A5=FN(ACT49P)   RETURN ACTIVITY 5 FROM FUNCTION
        BLET          &A6=FN(ACT49P)   RETURN ACTIVITY 6 FROM FUNCTION
        BLET          &A7=FN(ACT49P)   RETURN ACTIVITY 7 FROM FUNCTION
        BLET          &A8=FN(ACT49P)   RETURN ACTIVITY 8 FROM FUNCTION
        BLET          &A9=FN(ACT49P)   RETURN ACTIVITY 9 FROM FUNCTION
        TEST NE       &C1,9,DONE       IF 10-12 ACTS/DAY CONT, OTHERWISE GO2 DONE
        BLET          &A10=FN(ACT49P)  RETURN ACTIVITY 10 FROM FUNCTION
        TEST NE       &C1,10,DONE      IF 11,12 ACTS/DAY CONT., OTHERWISE GO2 DONE
        BLET          &A11=FN(ACT49P)  RETURN ACTIVITY 11 FROM FUNCTION
        TEST NE       &C1,11,DONE      IF 12 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET          &A12=FN(ACT49P)  RETURN ACTIVITY 12 FROM FUNCTION
        TRANSFER      ,DONE
*
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*   Cluster 5
*
CLU5    TEST E      PB(CNO),5,CLU6     IF IN CLUSTER 5 CONT., OTHERWISE GO2 CLU6
        BLET        &C1=FN(DAY5)       THE # OF ACTS./DAT FOR CLUSTER 5
        BLET        &P=FN(TRV5)        RETURNS THE % ACTS WHICH NEED TRAVEL
NXT54   TEST LE     &C1,4,NXT55        IF 2-4 ACTS/DAT CONT, OTHERWISE GO2 NXT55
        BLET        &A1=FN(ACT504)     RETURN ACTIVITY 1 FROM FUNCTION
        BLET        &A2=FN(ACT504)     RETURN ACTIVITY 2 FROM FUNCTION
        TEST NE     &C1,2,DONE         IF 3,4 ACTS/DAY CONT, OTHERWISE GO2 DONE
        BLET        &A3=FN(ACT504)     RETURN ACTIVITY 3 FROM FUNCTION
        TEST NE     &C1,3,DONE         IF 4 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET        &A4=FN(ACT504)     RETURN ACTIVITY 4 FROM FUNCTION
        TRANSFER    ,DONE
NXT55   TEST LE     &C1,6,NXT57        IF 5,6 ACTS/DAY CONT, OTHERWISE GO2 NXT57
        BLET        &A1=FN(ACT556)     RETURN ACTIVITY 1 FROM FUNCTION
        BLET        &A2=FN(ACT556)     RETURN ACTIVITY 2 FROM FUNCTION
        BLET        &A3=FN(ACT556)     RETURN ACTIVITY 3 FROM FUNCTION
        BLET        &A4=FN(ACT556)     RETURN ACTIVITY 4 FROM FUNCTION
        BLET        &A5=FN(ACT556)     RETURN ACTIVITY 5 FROM FUNCTION
        TEST NE     &C1,5,DONE         IF 6 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET        &A6=FN(ACT556)     RETURN ACTIVITY 6 FROM FUNCTION
        TRANSFER    ,DONE
NXT57   TEST LE     &C1,8,NXT59        IF 7,8 ACTS/DAY CONT., OTHERWISE GO2 NXT59
        BLET        &A1=FN(ACT578)     RETURN ACTIVITY 1 FROM FUNCTION
        BLET        &A2=FN(ACT578)     RETURN ACTIVITY 2 FROM FUNCTION
        BLET        &A3=FN(ACT578)     RETURN ACTIVITY 3 FROM FUNCTION
        BLET        &A4=FN(ACT578)     RETURN ACTIVITY 4 FROM FUNCTION
        BLET        &A5=FN(ACT578)     RETURN ACTIVITY 5 FROM FUNCTION
        BLET        &A6=FN(ACT578)     RETURN ACTIVITY 6 FROM FUNCTION
        BLET        &A7=FN(ACT578)     RETURN ACTIVITY 7 FROM FUNCTION
        TEST NE     &C1,7,DONE         IF 8 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET        &A8=FN(ACT578)     RETURN ACTIVITY 8 FROM FUNCTION
        TRANSFER    ,DONE
NXT59   TEST LE     &C1,10,NXT511      IF 9,10 ACTS/DAY CONT., OTHERWISE GO2 NXT511
        BLET        &A1=FN(ACT591)     RETURN ACTIVITY 1 FROM FUNCTION
        BLET        &A2=FN(ACT591)     RETURN ACTIVITY 2 FROM FUNCTION
        BLET        &A3=FN(ACT591)     RETURN ACTIVITY 3 FROM FUNCTION
        BLET        &A4=FN(ACT591)     RETURN ACTIVITY 4 FROM FUNCTION
        BLET        &A5=FN(ACT591)     RETURN ACTIVITY 5 FROM FUNCTION
        BLET        &A6=FN(ACT591)     RETURN ACTIVITY 6 FROM FUNCTION
        BLET        &A7=FN(ACT591)     RETURN ACTIVITY 7 FROM FUNCTION
        BLET        &A8=FN(ACT591)     RETURN ACTIVITY 8 FROM FUNCTION
        BLET        &A9=FN(ACT591)     RETURN ACTIVITY 9 FROM FUNCTION
        TEST NE     &C1,9,DONE         IF 10 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET        &A10=FN(ACT591)    RETURN ACTIVITY 10 FROM FUNCTION
        TRANSFER    ,DONE
NXT511  TEST LE     &C1,12,DONE        IF 11,12 ACTS/DAY CONT, OTHERWISE GO2 DONE
        BLET        &A1=FN(ACT511)     RETURN ACTIVITY 1 FROM FUNCTION
        BLET        &A2=FN(ACT511)     RETURN ACTIVITY 2 FROM FUNCTION
        BLET        &A3=FN(ACT511)     RETURN ACTIVITY 3 FROM FUNCTION
        BLET        &A4=FN(ACT511)     RETURN ACTIVITY 4 FROM FUNCTION
        BLET        &A5=FN(ACT511)     RETURN ACTIVITY 5 FROM FUNCTION
        BLET        &A6=FN(ACT511)     RETURN ACTIVITY 6 FROM FUNCTION
        BLET        &A7=FN(ACT511)     RETURN ACTIVITY 7 FROM FUNCTION
        BLET        &A8=FN(ACT511)     RETURN ACTIVITY 8 FROM FUNCTION
        BLET        &A9=FN(ACT511)     RETURN ACTIVITY 9 FROM FUNCTION
        BLET        &A10=FN(ACT511)    RETURN ACTIVITY 10 FROM FUNCTION
        BLET        &A11=FN(ACT511)    RETURN ACTIVITY 11 FROM FUNCTION
        TEST NE     &C1,11,DONE        IF 12 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
        BLET        &A12=FN(ACT511)    RETURN ACTIVITY 12 FROM FUNCTION
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       TRANSFER          ,DONE
*
*  Cluster 6
*
CLU6   ADVANCE           0
       BLET              &C1=FN(DAY6)      THE # OF ACTS./DAT FOR CLUSTER 6
       BLET              &P=FN(TRV6)       RETURNS % ACTS WHICH NEED TRAVEL
NXT64  TEST LE           &C1,5,NXT66       IF 2-5 ACTS/DAT CONTINUE, OTHERWISE GO2 NXT63
       BLET              &A1=FN(ACT605)    RETURN ACTIVITY 1 FROM FUNCTION
       BLET              &A2=FN(ACT605)    RETURN ACTIVITY 2 FROM FUNCTION
       TEST NE           &C1,2,DONE        IF 3-5 ACTS/DAY CONT., OTHERWISE GO2 DONE
       BLET              &A3=FN(ACT605)    RETURN ACTIVITY 3 FROM FUNCTION
       TEST NE           &C1,3,DONE        IF 4,5 ACTS/DAY CONT., OTHERWISE GO2 DONE
       BLET              &A4=FN(ACT605)    RETURN ACTIVITY 4 FROM FUNCTION
       TEST NE           &C1,4,DONE        IF 5 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
       BLET              &A5=FN(ACT605)    RETURN ACTIVITY 5 FROM FUNCTION
       TRANSFER          ,DONE
NXT66  TEST LE           &C1,8,NXT69       IF 6-8 ACTS/DAY CONT, OTHERWISE GO2 DONE
       BLET              &A1=FN(ACT668)    RETURN ACTIVITY 1 FROM FUNCTION
       BLET              &A2=FN(ACT668)    RETURN ACTIVITY 2 FROM FUNCTION
       BLET              &A3=FN(ACT668)    RETURN ACTIVITY 3 FROM FUNCTION
       BLET              &A4=FN(ACT668)    RETURN ACTIVITY 4 FROM FUNCTION
       BLET              &A5=FN(ACT668)    RETURN ACTIVITY 5 FROM FUNCTION
       BLET              &A6=FN(ACT668)    RETURN ACTIVITY 6 FROM FUNCTION
       TEST NE           &C1,6,DONE        IF 7,8 ACTS/DAY CONT, OTHERWISE GO2 DONE
       BLET              &A7=FN(ACT668)    RETURN ACTIVITY 7 FROM FUNCTION
       TEST NE           &C1,7,DONE        IF 8 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
       BLET              &A8=FN(ACT668)    RETURN ACTIVITY 8 FROM FUNCTION
       TRANSFER          ,DONE
NXT69  TEST LE           &C1,12,DONE       IF 9-12 ACTS/DAY CONT, OTHERWISE GO2 DONE
       BLET              &A1=FN(ACT69P)    RETURN ACTIVITY 1 FROM FUNCTION
       BLET              &A2=FN(ACT69P)    RETURN ACTIVITY 2 FROM FUNCTION
       BLET              &A3=FN(ACT69P)    RETURN ACTIVITY 3 FROM FUNCTION
       BLET              &A4=FN(ACT69P)    RETURN ACTIVITY 4 FROM FUNCTION
       BLET              &A5=FN(ACT69P)    RETURN ACTIVITY 5 FROM FUNCTION
       BLET              &A6=FN(ACT69P)    RETURN ACTIVITY 6 FROM FUNCTION
       BLET              &A7=FN(ACT69P)    RETURN ACTIVITY 7 FROM FUNCTION
       BLET              &A8=FN(ACT69P)    RETURN ACTIVITY 8 FROM FUNCTION
       BLET              &A9=FN(ACT69P)    RETURN ACTIVITY 9 FROM FUNCTION
       TEST NE           &C1,9,DONE        IF 10-12 ACTS/DAY CONT, OTHERWISE GO2 DONE
       BLET              &A10=FN(ACT69P)   RETURN ACTIVITY 10 FROM FUNCTION
       TEST NE           &C1,10,DONE       IF 11,12 ACTS/DAY CONT, OTHERWISE GO2 DONE
       BLET              &A11=FN(ACT69P)   RETURN ACTIVITY 11 FROM FUNCTION
       TEST NE           &C1,11,DONE       IF 12 ACTS/DAY CONTINUE, OTHERWISE GO2 DONE
       BLET              &A12=FN(ACT69P)   RETURN ACTIVITY 12 FROM FUNCTION
       TRANSFER          ,DONE
*
*
*
DONE   BLET              &C2=&P*&C1        GIVES # ACTS THAT REQUIRE TRAVEL (REAL #)
       BLET              &C3=FN(RND)       ROUNDS &C2 OFF TO NEAREST INTEGER
*
*
* Summarize the number of activities which require travel:
*
       ASSIGN            1,&A1,PB
       ASSIGN            2,&A2,PB
       ASSIGN            3,&A3,PB
       ASSIGN            4,&A4,PB
       ASSIGN            5,&A5,PB
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       ASSIGN          6,&A6,PB
       ASSIGN          7,&A7,PB
       ASSIGN          8,&A8,PB
       ASSIGN          9,&A9,PB
       ASSIGN          10,&A10,PB
       ASSIGN          11,&A11,PB
       ASSIGN          12,&A12,PB
       BLET            &T1=0
       BLET            &T2=0
       BLET            &T3=0
       BLET            &T4=0
       BLET            &T5=0
       BLET            &T6=0
       BLET            &T7=0
       BLET            &T8=0
       BLET            &X=1
LOOP1  TEST GE         PB(&X),11,LOOP2
       TEST E          PB(&X),11,LP1
       BLET            &T1=&T1+1
LP1    TEST E          PB(&X),12,LP2
       BLET            &T2=&T2+1
LP2    TEST E          PB(&X),13,LP3
       BLET            &T3=&T3+1
LP3    TEST E          PB(&X),14,LP4
       BLET            &T4=&T4+1
LP4    TEST E          PB(&X),15,LP5
       BLET            &T5=&T5+1
LP5    TEST E          PB(&X),16,LP6
       BLET            &T6=&T6+1
LP6    TEST E          PB(&X),17,LP7
       BLET            &T7=&T7+1
LP7    TEST E          PB(&X),18,LOOP2
       BLET            &T8=&T8+1
LOOP2  BLET            &X=&X+1
       TEST LE         &X,12,LOOP3
       TRANSFER        ,LOOP1
*
LOOP3  ADVANCE         0
*
       BLET            &Y=&T1+&T2+&T3+&T4+&T5+&T6+&T7+&T8   lets &Y be the # acts req. travl
       TEST NE         &Y,&C3,LOOP9          Tests if have right number of acts that
* require travel, if not, send back to reassign acts from functions
GOBAK  TEST NE         PB(CNO),1,NEXT4
       TEST NE         PB(CNO),2,NXT24
       TEST NE         PB(CNO),3,NXT34
       TEST NE         PB(CNO),4,NXT44
       TEST NE         PB(CNO),5,NXT54
       TEST NE         PB(CNO),6,NXT64
*
*
*   HEURISTIC RULES DEIFNED:    -maximum values for each of the 8 activity classes
*                               -max. values are acts. per day with AND without travel
*
LOOP9  BLET            &U1=0      U values will be totl # of acts w/o travel
       BLET            &U2=0
       BLET            &U3=0
       BLET            &U4=0
       BLET            &U5=0
       BLET            &U6=0
       BLET            &U7=0
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       BLET                 &U8=0
       BLET                 &Z=1
LOOQ1  TEST LE              PB(&Z),8,LOOQ2
       TEST E               PB(&Z),1,LQ1
       BLET                 &U1=&U1+1
LQ1    TEST E               PB(&Z),2,LQ2
       BLET                 &U2=&U2+1
LQ2    TEST E               PB(&Z),3,LQ3
       BLET                 &U3=&U3+1
LQ3    TEST E               PB(&Z),4,LQ4
       BLET                 &U4=&U4+1
LQ4    TEST E               PB(&Z),5,LQ5
       BLET                 &U5=&U5+1
LQ5    TEST E               PB(&Z),6,LQ6
       BLET                 &U6=&U6+1
LQ6    TEST E               PB(&Z),7,LQ7
       BLET                 &U7=&U7+1
LQ7    TEST E               PB(&Z),8,LOOQ2
       BLET                 &U8=&U8+1
LOOQ2  BLET                 &Z=&Z+1
       TEST LE              &Z,12,LOOQ3
       TRANSFER             ,LOOQ1
*
LOOQ3  ADVANCE              0
       BLET                 &V1=&T1+&U1      Totl number of meals (with and w/o travl)
       BLET                 &V2=&T2+&U2      Totl number of subst (with and w/o travl)
       BLET                 &V3=&T3+&U3      Totl number of house (with and w/o travl)
       BLET                 &V4=&T4+&U4      Totl number of prsnl (with and w/o travl)
       BLET                 &V5=&T5+&U5      Totl number of socl  (with and w/o travl)
       BLET                 &V6=&T6+&U6      Totl number of amuse (with and w/o travl)
       BLET                 &V7=&T7+&U7      Totl number of recr  (with and w/o travl)
       BLET                 &V8=&T8+&U8      Totl number of other (with and w/o travl)
       TEST LE              &V1,5,GOBAK      RULE: max. Meals =5  -otherwise go back to fn.
       TEST NE              PB(CNO),1,YYY
       TEST LE              &V2,2,GOBAK      RULE: max subst. =2 for clusters 2-6
YYY    TEST LE              &V2,5,GOBAK      RULE: max subst =5 for cluster 1
       TEST LE              &V3,7,GOBAK      RULE: max house =7
       TEST LE              &V4,2,GOBAK      RULE: max persnl =2
       TEST LE              &V5,3,GOBAK      RULE: max social =3
       TEST LE              &V6,6,GOBAK      RULE: max amuse =6
       TEST LE              &V7,4,GOBAK      RULE: max recrtn =4
       TEST LE              &V8,3,GOBAK      RULE: max other =3
*
*
*  TRIP TOURS DEVELOPED.
*
*
       TEST E               PB(CNO),1,LLP1
       BLET                 &TR=0.283+(0.457*&T1)+(0.110*&T2)+(0.198*&T3)_
+(0.333*&T4)+(0.483*&T5)+(0.416*&T6)+(0.494*&T7)+(0.252*&T8)
LLP1   TEST E               PB(CNO),2,LLP2
       BLET                 &TR=0.182+(0.369*&T1)+(0.438*&T2)+(0.283*&T3)_
+(0.318*&T5)+(0.369*&T6)+(0.495*&T7)+(0.228*&T8)
LLP2   TEST E               PB(CNO),3,LLP3
       BLET                 &TR=0.056+(0.218*&T1)+(0.604*&T2)+(0.299*&T3)_
+(0.273*&T4)+(0.662*&T5)+(0.562*&T6)+(0.271*&T7)+(0.396*&T8)
LLP3   TEST E               PB(CNO),4,LLP4
       BLET                 &TR=0.076+(0.277*&T1)+(0.492*&T2)+(0.337*&T3)_
+(0.189*&T4)+(0.379*&T5)+(0.483*&T6)+(0.381*&T7)+(0.125*&T8)
LLP4   TEST E               PB(CNO),5,LLP5
```

```
       BLET              &TR=0.110+(0.400*&T1)+(0.257*&T2)+(0.287*&T3)_
+(0.226*&T4)+(0.272*&T5)+(0.429*&T6)+(0.591*&T7)+(0.355*&T8)
LLP5   TEST E            PB(CNO),6,DONE2
       BLET              &TR=0.074+(0.487*&T1)+(0.230*&T3)+(0.174*&T5)_
+(0.393*&T6)+(0.869*&T7)+(0.367*&T8)
*
DONE2 ADVANCE            0
*


*
* MODE SPLIT ASSIGNMENTS
*
       BLET              &M1=0
       BLET              &M2=0
       BLET              &M3=0
       BLET              &M4=0
       BLET              &M5=0
       BLET              &M6=0
       TEST GE           &TR,0.500,SKIP     if tours are <0.500 skip mode assignment
       TEST E            PB(CNO),1,MD2      if cluster1 con't, otherwise go2 MD2
       TEST E            &T7,0,REC1         if at least 1 trav acts=recr, goto REC1
       BLET              &M1=FN(MOD1)       return mode for 1st tour from function
ONE1   TEST G            &TR,1.500,SKIP     if at least 2 tours carry on
       BLET              &M2=FN(MOD1)
       TEST G            &TR,2.500,SKIP     if at least 3 tours carry on
       BLET              &M3=FN(MOD1)
       TEST G            &TR,3.500,SKIP     if at least 4 tours carry on
       BLET              &M4=FN(MOD1)
       TEST G            &TR,4.500,SKIP     if at least 5 tours carry on
       BLET              &M5=FN(MOD1)
       TEST G            &TR,5.500,SKIP     if at least 6 tours carry on
       BLET              &M6=FN(MOD1)
       TRANSFER          ,SKIP
REC1   BLET              &M1=FN(MOD1R)      if at least 1 rec. act. assign mode by MOD1R fn
       TRANSFER          ,ONE1
MD2    TEST E            PB(CNO),2,MD3      if cluster 2 con't, otherwise go2 MD3
       TEST E            &T7,0,REC2         if at least 1 trav acts=recr, goto REC2
       BLET              &M1=FN(MOD2)       return mode for 1st tour from function
ONE2   TEST G            &TR,1.500,SKIP     if at least 2 tours carry on
       BLET              &M2=FN(MOD2)
       TEST G            &TR,2.500,SKIP     if at least 3 tours carry on
       BLET              &M3=FN(MOD2)
       TEST G            &TR,3.500,SKIP     if at least 4 tours carry on
       BLET              &M4=FN(MOD2)
       TEST G            &TR,4.500,SKIP     if at least 5 tours carry on
       BLET              &M5=FN(MOD2)
       TEST G            &TR,5.500,SKIP     if at least 6 tours carry on
       BLET              &M6=FN(MOD2)
       TRANSFER          ,SKIP
REC2   BLET              &M1=FN(MOD2R)      if at least 1 rec. act. assign mode by MOD1R fn
       TRANSFER          ,ONE2
MD3    TEST E            PB(CNO),3,MD4      if cluster 3 con't, otherwise go2 MD4
       TEST E            &T7,0,REC3         if at least 1 trav acts=recr, goto REC3
       BLET              &M1=FN(MOD3)       return mode for 1st tour from function
ONE3   TEST G            &TR,1.500,SKIP     if at least 2 tours carry on
       BLET              &M2=FN(MOD3)
       TEST G            &TR,2.500,SKIP     if at least 3 tours carry on
       BLET              &M3=FN(MOD3)
       TEST G            &TR,3.500,SKIP     if at least 4 tours carry on
       BLET              &M4=FN(MOD3)
```

```
        TEST G      &TR,4.500,SKIP    if at least 5 tours carry on
        BLET        &M5=FN(MOD3)
        TEST G      &TR,5.500,SKIP    if at least 6 tours carry on
        BLET        &M6=FN(MOD3)
        TRANSFER    ,SKIP
REC3    BLET        &M1=FN(MOD3R)     if at least 1 rec. act. assign mode by MOD1R fn
        TRANSFER    ,ONE3
MD4     TEST E      PB(CNO),4,MD5     if cluster 4 con't, otherwise go2 MD5
        TEST E      &T7,0,REC4        if at least 1 trav acts=recr, goto REC4
        BLET        &M1=FN(MOD4)      return mode for 1st tour from function
ONE4    TEST G      &TR,1.500,SKIP    if at least 2 tours carry on
        BLET        &M2=FN(MOD4)
        TEST G      &TR,2.500,SKIP    if at least 3 tours carry on
        BLET        &M3=FN(MOD4)
        TEST G      &TR,3.500,SKIP    if at least 4 tours carry on
        BLET        &M4=FN(MOD4)
        TEST G      &TR,4.500,SKIP    if at least 5 tours carry on
        BLET        &M5=FN(MOD4)
        TEST G      &TR,5.500,SKIP    if at least 6 tours carry on
        BLET        &M6=FN(MOD4)
        TRANSFER    ,SKIP
REC4    BLET        &M1=FN(MOD4R)     if at least 1 rec. act. assign mode by MOD1R fn
        TRANSFER    ,ONE4
MD5     TEST E      PB(CNO),5,MD6     if cluster 5 con't, otherwise go2 MD6
        TEST E      &T7,0,REC5        if at least 1 trav acts=recr, goto REC5
        BLET        &M1=FN(MOD5)      return mode for 1st tour from function
ONE5    TEST G      &TR,1.500,SKIP    if at least 2 tours carry on
        BLET        &M2=FN(MOD5)
        TEST G      &TR,2.500,SKIP    if at least 3 tours carry on
        BLET        &M3=FN(MOD5)
        TEST G      &TR,3.500,SKIP    if at least 4 tours carry on
        BLET        &M4=FN(MOD5)
        TEST G      &TR,4.500,SKIP    if at least 5 tours carry on
        BLET        &M5=FN(MOD5)
        TEST G      &TR,5.500,SKIP    if at least 6 tours carry on
        BLET        &M6=FN(MOD5)
        TRANSFER    ,SKIP
REC5    BLET        &M1=FN(MOD5R)     if at least 1 rec. act. assign mode by MOD1R fn
        TRANSFER    ,ONE5
MD6     TEST E      PB(CNO),6,SKIP    if cluster 6 con't, otherwise go2 SKIP
        TEST E      &T7,0,REC6        if at least 1 trav acts=recr, goto REC6
        BLET        &M1=FN(MOD6)      return mode for 1st tour from function
ONE6    TEST G      &TR,1.500,SKIP    if at least 2 tours carry on
        BLET        &M2=FN(MOD6)
        TEST G      &TR,2.500,SKIP    if at least 3 tours carry on
        BLET        &M3=FN(MOD6)
        TEST G      &TR,3.500,SKIP    if at least 4 tours carry on
        BLET        &M4=FN(MOD6)
        TEST G      &TR,4.500,SKIP    if at least 5 tours carry on
        BLET        &M5=FN(MOD6)
        TEST G      &TR,5.500,SKIP    if at least 6 tours carry on
        BLET        &M6=FN(MOD6)
        TRANSFER    ,SKIP
REC6    BLET        &M1=FN(MOD6R)     if at least 1 rec. act. assign mode by MOD1R fn
        TRANSFER    ,ONE6
*
SKIP    ADVANCE     0
        BPUTPIC     FILE=TRAVL,(PB(CNO),&T1,&T2,&T3,&T4,&T5,&T6,&T7,_
&T8,&TR)
* * * * * * * * * * * * *.**
```

```
      BPUTPIC          FILE=ACTS,(PB(CNO),&TR,&C1,&C3,&A1,&A2,&A3,&A4,&A5,&A6,_
&A7,&A8,&A9,&A10,&A11,&A12)
* *.** * * * * * * * * * * * * * *
*NOTE: need enough asterisks above (1 for each variable in output file)
*
      BPUTPIC          FILE=CHEK,(PB(CNO),&C1,&V1,&V2,&V3,&V4,&V5,&V6,&V7,&V8)
* * * * * * * * * *
      BPUTPIC          FILE=MODES,(PB(CNO),&C1,&TR,&T7,&M1,&M2,&M3,&M4,&M5,&M6)
* * *.** * * * * * * *
      TERMINATE        1
      START            1150
      END
```

Appendix D

Distributions of Activities by Class for Lifestyle Clusters

Distribution of Activities by Class for *Mobile Widows* Cluster

Activity Classes		Activities per Day				
		0-4	5-6	7-8	9-10	11+
meals	without travel	12.7%	20.7%	19.6%	20.0%	18.3%
	with travel	8.0%	7.9%	7.9%	6.9%	5.5%
subsistence	without travel	0%	0.3%	0.1%	0.3%	0.2%
	with travel	0%	0.6%	0.7%	0.3%	0.4%
house maintenance	without travel	9.7%	11.2%	10.8%	13.2%	12.8%
	with travel	11.9%	11.9%	14.2%	13.6%	13.4%
personal maintenance	without travel	0%	0%	0.2%	0.2%	0.5%
	with travel	1.7%	1.9%	1.8%	1.7%	1.7%
social	without travel	1.7%	2.9%	2.6%	4.1%	3.7%
	with travel	6.4%	4.8%	4.1%	4.1%	5.0%
amusement	without travel	24.8%	18.0%	21.3%	21.8%	22.7%
	with travel	8.7%	7.7%	6.7%	4.6%	5.3%
recreation	without travel	7.2%	3.7%	3.1%	2.1%	3.8%
	with travel	6.4%	6.1%	3.2%	4.0%	2.9%
other	without travel	0%	0%	0%	0%	0.1%
	with travel	0.8%	2.3%	3.7%	3.1%	3.7%
	Total	100.0%	100.0%	100.0%	100.0%	100.0%

Distribution of Activities by Class for the *Granny Flats* Cluster

Activity Classes		Activities per Day		
		0-5	6-7	8+
meals	without travel	22.5%	29.5%	25.8%
	with travel	4.0%	4.3%	4.0%
subsistence	without travel	0%	0.8%	0%
	with travel	1.0%	1.3%	0%
house maintenance	without travel	9.7%	10.2%	11.2%
	with travel	6.9%	6.8%	6.9%
personal maintenance	without travel	1.9%	0%	0%
	with travel	4.0%	0%	1.8%
social	without travel	0%	1.2%	1.4%
	with travel	1.9%	2.6%	1.1%
amusement	without travel	21.6%	33.1%	30.2%
	with travel	1.9%	1.7%	4.3%
recreation	without travel	18.5%	4.7%	5.0%
	with travel	4.0%	2.1%	2.2%
other	without travel	0%	0%	0%
	with travel	1.9%	1.7%	6.1%
	Total	100.0%	100.0%	100.0%

Distribution of Activities by Class for the *Mobility Impaired* Cluster

Activity Classes		Activities per Day			
		0-4	5-6	7-8	9+
meals	without travel	27.6%	28.7%	26.1%	24.5%
	with travel	5.2%	5.0%	4.5%	3.1%
subsistence	without travel	0%	0.3%	0.3%	0.6%
	with travel	3.4%	0.4%	0.4%	0.3%
house maintenance	without travel	5.2%	7.2%	8.7%	10.8%
	with travel	3.4%	5.6%	10.9%	7.5%
personal maintenance	without travel	0%	0%	0.4%	0.3%
	with travel	0%	1.9%	0.9%	1.2%
social	without travel	5.2%	2.6%	4.8%	5.7%
	with travel	1.7%	4.6%	1.9%	2.1%
amusement	without travel	37.9%	25.9%	27.1%	27.8%
	with travel	5.2%	5.8%	3.1%	4.7%
recreation	without travel	5.2%	9.4%	6.9%	7.4%
	with travel	0%	2.2%	2.9%	2.4%
other	without travel	0%	0%	0%	0.3%
	with travel	0%	0.4%	1.2%	1.3%
	Total	100.0%	100.0%	100.0%	100.0%

Distribution of Activities by Class for the *Affluent Males* Cluster

Activity Classes		Activities per Day				
		0-4	5-6	7-8	9-10	11+
meals	without travel	10.4%	19.1%	19.9%	19.3%	18.0%
	with travel	8.2%	8.0%	7.3%	7.3%	5.3%
subsistence	without travel	0.3%	0.5%	0%	0.1%	0.1%
	with travel	1.5%	0.4%	0.3%	0%	0.7%
house maintenance	without travel	5.7%	11.5%	10.0%	11.5%	11.7%
	with travel	11.7%	11.2%	13.1%	14.4%	13.0%
personal maintenance	without travel	1.0%	0.2%	0%	0.1%	0%
	with travel	2.9%	1.5%	1.4%	2.2%	2.2%
social	without travel	3.4%	1.6%	2.5%	3.3%	4.2%
	with travel	4.4%	4.5%	4.5%	3.6%	3.5%
amusement	without travel	17.3%	21.3%	22.2%	21.1%	27.8%
	with travel	14.0%	9.1%	7.1%	5.7%	4.2%
recreation	without travel	4.4%	3.1%	4.4%	3.7%	4.4%
	with travel	9.1%	6.0%	4.0%	4.6%	3.3%
other	without travel	0%	0%	0%	0%	0%
	with travel	5.7%	2.0%	3.3%	3.1%	1.6%
	Total	100.0%	100.0%	100.0%	100.0%	100.0%

Distribution of Activities by Class for the *Disabled Drivers* Cluster

Activity Classes		Activities per Day		
		0-5	6-8	9+
meals	without travel	16.8%	24.7%	21.0%
	with travel	10.9%	6.3%	5.0%
subsistence	without travel	0%	0%	0%
	with travel	0%	0%	0.3%
house maintenance	without travel	7.9%	10.9%	11.1%
	with travel	9.9%	9.5%	14.1%
personal maintenance	without travel	0%	0.3%	0%
	with travel	4.0%	2.5%	0.8%
social	without travel	1.9%	3.3%	2.4%
	with travel	0%	3.0%	4.2%
amusement	without travel	19.9%	24.6%	28.4%
	with travel	9.9%	3.8%	4.5%
recreation	without travel	11.8%	6.9%	5.8%
	with travel	4.0%	2.1%	1.1%
other	without travel	0%	0%	0%
	with travel	3.0%	2.1%	1.3%
	Total	100.0%	100.0%	100.0%

Appendix E

Cumulative Distributions of Activity Engagement

Frequency of Activity Engagement by Activity Class
***Workers* Cluster**
(N = 1125 survey respondents x 2 days = 250)

Percentile:	Activity Classes							
	meals	substn.	house maint.	persnl maint.	social	amsemnt	recreatn	other
95th	3	4	4	-	-	4	2	2
99th	4	5	6	-	2	5	-	3
99.5th	-	-	7	1	-	6	3	-
100th	5	6	8	2	3	7	4	4

Frequency of Activity Engagement by Activity Class
***Mobile Widows* Cluster**
(N = 337 survey respondents x 2 days = 674)

Percentile:	Activity Classes							
	meals	substn.	house maint.	persnl maint.	social	amsemnt	recreatn	other
95th	4	0	5	1	2	5	2	2
99th	-	1	7	-	3	-	-	3
99.5th	5	2	-	2	4	6	3	-
100th	8	3	8	3	5	9	6	4

Frequency of Activity Engagement by Activity Class
***Granny Flats* Cluster**
(N = 50 survey respondents x 2 days = 100)

Percentile:	Activity Classes							
	meals	substn.	house maint.	persnl maint.	social	amsemnt	recreatn	other
95th	3	0	3	-	1	5	2	1
99th	4	2	5	1	-	-	-	4
99.5th	-	-	-	-	-	-	-	-
100th	5	3	6	2	2	6	3	5

Frequency of Activity Engagement by Activity Class
***Mobility Impaired* Cluster**
(N = 141 survey respondents x 2 days = 282)

Percentile:	Activity Classes							
	meals	substn.	house maint.	persnl maint.	social	amsemnt	recreatn	other
95th	4	-	3	1	2	5	3	-
99th	-	-	5	-	-	-	-	1
99.5th	-	1	-	-	-	6	-	3
100th	5	2	6	2	4	8	4	4

Frequency of Activity Engagement by Activity Class
***Affluent Males* Cluster**
(N = 436 survey respondents x 2 days = 872)

Percentile:	Activity Classes							
	meals	substn.	house maint.	persnl maint.	social	amsemnt	recreatn	other
95th	3	-	4	1	2	4	2	1
99th	-	1	-	-	3	-	-	-
99.5th	4	-	6	2	4	6	3	-
100th	5	2	8	3	5	8	4	2

Frequency of Activity Engagement by Activity Class
***Disabled Rivers* Cluster**
(N = 61 survey respondents x 2 days = 122)

Percentile:	Activity Classes							
	meals	substn.	house maint.	persnl maint.	social	amsemnt	recreatn	other
95th	3	-	4	-	2	-	2	1
99th	4	0	6	1	3	5	3	2
99.5th	-	-	-	-	-	-	-	-
100th	5	1	8	2	4	6	4	3

GLOSSARY

AMOS	Activity-Mobility Simulator.
ANOVA	Analysis of Variance.
CAAA	Clean Air Act Amendment.
d.f.	Statistical degrees of freedom.
FHWA	Federal Highway Administration.
GIS	Geographic Information System.
GPSS/H	General Purpose Simulation Software.
HATS	Household Activity Travel Simulator.
ISTEA	Intermodal Surface Transportation Efficiency Act.
ITE	Institute of Transportation Engineers.
ITS	Intelligent Transportation Systems.
MASTER	Micro-Analytical Simulation of Transport, Employment and Residence.
MAX	Portland's light rail system.
MCA	Multiple Classification Analysis.
MIDAS	Micro-Analytical Integrated Demographic Accounting System.
MPO	Metropolitan Planning Organization.
MUVI	MIDAS-USA-Version 1.
MWCOG	Metropolitan Washington Council of Governments.
N	Sample size.
NPTS	Nationwide Personal Transportation Study.
SPSS	Statistical Package for the Social Sciences.
TCM	Travel Control Measures.
TDM	Travel Demand Management.
TMIP	Travel Model Improvement Program.
TRANSIMS	Transportation Analysis and Simulation System.
TRB	Transportation Research Board.
UPGMA	Unweighted Pair-Group Method.
UTPS	Urban Transportation Planning System.
VIF	Variance Inflation Factor.

IMAGE EVALUATION TEST TARGET (QA-3)

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6″

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