IMPACT: An Integrated GIS-Based Model for Population Aging Consequences on Transportation

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Abstract

Recent advancements in computing and Geographic Information Systems (GIS) have revolutionized the development of decision support systems (DSS) to study and simulate the future of travel demand in urban areas. While travel demand models have been widely developed and used to inform the urban planning process, very little has been done to explicitly account for the aging of population within such models. In this paper, we report on the development of IMPACT (Integrated Model for Population Aging Consequences on Transportation), a GIS-based decision support system (DSS) capable of assessing the ramifications of population aging on the performance and usage of the urban transportation system. As a geo-spatial DSS, the model is developed as a stand-alone GIS-T platform using components from the ESRI MapObjects software. To account for the aging of population during simulations, a demographic model is formulated and integrated with the travel demand model. The latter simulates travel flows on the road network of the city given the simulated demographic characteristics of drivers. The model is calibrated using 1996 and 2001 data that are obtained for the Census Metropolitan Area of Hamilton in Ontario, Canada. A key feature of the developed model is its ability to tease out the impacts of population aging on urban travel.

Keywords: Demography, elderly, MapObjects, simulation, travel demand, Hamilton

1. Introduction

Over the past five decades, most North American cities became progressively more dependent on the automobile. As a result, road traffic and the associated levels of tail pipe emissions and energy (gasoline) consumption are growing at an alarming rate. This has been accompanied by massive capital investments in road infrastructure, which is still a common practice in the planning of cities. Urban transport planners and practitioners sought tools to conduct cost-benefit analysis of such infrastructure investment projects. Consequently, the trip-based four-stage Urban Transportation Modeling System (UTMS) was adopted by most metropolitan planning organizations (Meyer and Miller, 2001). To date, UTMS is used, as the state of practice tool, to project future traffic and evaluate the need for new road capacity. It also plays a major role in assessing changes in transit service and land use patterns in cities around the globe. It has done so by mainly focusing on peak-period, work related travel.

UTMS has normally ignored the contribution of older retired drivers on the urban transportation system. However, with the aging of population in most developed countries, the number and percentage of older drivers in urban areas is on the rise. Statistics Canada (2002) estimates that by 2021 one in five Canadians will be at least 65 years old. Research for the United States, Australia and some European countries provides evidence suggesting that as people age they become more dependent on the automobile (Rosenbloom, 2001). A recent study by Newbold et al. (2005) on travel behavior within Canada’s older population for the periods 1986, 1992 and 1998 provides findings that are
inline with those of Rosenbloom (2001). The general findings indicate that while older Canadians undertake fewer trips, their dependence on the automobile for mobility is no less significant when compared to young drivers who are economically active. Newbold et al. (2005) found that the number of trips by car for older drivers appear to increase from 1986 to 1998 as the population ages. To date, very little has been done to address the relationship between population aging and the future of travel in the Canadian context. There have been no previous efforts to assess scenarios of how population aging will impact the urban transportation system in the future. This is due to the lack of appropriate simulation models that are capable of simulating the aging of population and accounting for the travel behavior of elderly drivers when simulating future travel demand. This suggests the need to develop such models that are able to explicitly account for the aging of population while simulating travel on the road network of an urban area.

This paper reports on the work that was undertaken to develop IMPACT (Integrated Model for Population Aging Consequences on Transportation), a GIS-based decision support system (DSS) capable of assessing the ramifications of population aging on the urban transportation system. While the approach we describe has general applicability, we focus our attention to an application for the Hamilton Census Metropolitan Area (CMA) in Canada (Figure 1). The significance of our work is threefold. First, unlike most of the existing travel demand UTMS, the foundation of the devised system is a multiregional demographic model (MRDM) that is integrated with the UTMS. The demographic model ages the population over time using vital statistics (fertility, mortality and migration trends) that are available by age and sex (Rogers, 1995). A Spatial Aggregate Multinomial Logit Model (SAMNL) is also used to extend the demographic model and enables it to produce small area projections (Kanaroglou et al., 2007). That is, the demographic model is capable of updating the spatial distribution of population by sex and age in the traffic analysis zones (TAZs) of the CMA. Second, the trip generation component of the transportation system is based on an ordered-probit model that is estimated with disaggregate (individual) travel data (Páez et al., 2006). The ordered model provided a more robust and behavioral approach to overcome many of the inherent limitations that exist in the zone-based linear regression trip generation models commonly used within UTMS. It also facilitated the integration of the demographic and transportation systems and made the latter more responsive to demographic changes. Third, similar to the approach adopted in Buliung et al. (2005), the system is developed as a stand-alone GIS-based tool using components from the ESRI MapObjects software. The latter enables interactive specification of demographic and travel demand scenarios via map driven and spreadsheet dialogue boxes. IMPACT is made operational with demographic and travel data that were obtained from the population census of Statistics Canada and the Transportation Tomorrow Survey (TTS) of the Joint Program in Transportation at the University of Toronto, respectively.

**Figure 1 here**
The remainder of the paper is organized as follows. Section two starts with a background to provide an overview of the basic elements comprising a travel demand UTMS. It also sheds light on the significant role that Geographic Information System (GIS) can play to enhance the performance of these spatially oriented urban transportation-planning tools. Section three describes the general structure of the devised system and discusses in some detail the different components used in its development. Section four discusses the development environment of the system and illustrates the nature of output it is capable of producing given a simulation run for the period 1996 and 2051. Finally, the last section provides a conclusion of the paper.

2. Background

Travel demand modeling continues to be one of the most important elements of the urban transport planning process. The common practice for travel demand modeling is to use an Urban Transport Modeling System (UTMS) to simulate travel behavior in the city’s transport network. UTMS is conceived as a predictive model since its purpose is to predict the possible outcomes of alternative policies. Early versions of such model appeared in the mid 1950s and its use became commonplace by many metropolitan areas around the world by the 1960s (Southworth, 1995). Typically, the UTMS, known also as the four-stage model, consists of four sub-models that are executed sequentially. These are: trip generation, trip distribution, modal split and traffic assignment. The model starts with an exogenous distribution of land uses, population, employment and other economic activities for a particular base year. Therefore, the UTMS makes the assumption that land use planning is the main force driving the performance of the transportation system. In other words, the spatial distribution of population and jobs in a city gives rise to the observed transportation flows in the urban area.

Within an UTMS, the metropolitan area is represented with two layers of exogenous information: (1) a set of mutually exclusive zones known as Traffic Analysis Zones (TAZs), and (2) a set of connected links to represent the city’s transportation network. The trip generation submodel utilizes the exogenous land use information to determine the number of trips, usually classified by purpose (e.g. work, school, discretionary), originating from each TAZ as well as the number of trips destined to each TAZ. Trip generation models are typically based on either linear regression models or categorical data analysis (Kanaroglou and Scott, 2002). In recent years, more elaborate methods that rely on the ordered logit/probit models were used to enhance the predictive ability of trip generation models (see for example the work of Páez et al. 2006). Unlike linear regression models, which use the TAZ as the unit of analysis to explain and predict the generated trips, an ordered logit/probit model uses the household or a member of the household as the unit of analysis to explain the generated trips pertaining to that household or its members. The sole focus here is to explicitly account for the behavior of individual travelers within the model. Predicted trips per individual within any given TAZ are added up to determine the total trips generated from that TAZ. Further details on such an approach are provided in the next section.
The trip distribution submodel uses the information produced by the trip generation submodel to generate a set of zonal origin-destination (O-D) trip matrices by trip purpose and time of day. These O-D matrices describe the flows between all pairs of TAZs. Gravity based spatial interaction models and multinomial logit models are usually used to formulate trip distribution models (Ortuzar and Willumsen, 2001). Once the trip distribution submodel is executed, the modal split submodel accepts purpose-specific O-D matrices and splits them by travel mode (motorized, passenger, transit, walking, etc.). The multinomial logit and nested logit models are the most commonly used methods to perform a modal split (Ben-Akiva and Lerman, 1985; Hensher et al. 2005; Ortuzar and Willumsen, 2001).

Once the modal split submodel is executed, all purpose-specific motorized O-D trip matrices that relate to the same time of day are added up. The resulting matrix serves as input to the traffic assignment sub-model. The objective at this stage is to translate the zonal O-D flows into link flows, that is, flows that take place on the road network of the city. Several algorithms have been developed for this purpose, including the all-or-nothing (AON), user equilibrium (UE) and stochastic user equilibrium (SUE) algorithms (Sheffi, 1985). However, it has been shown that in the case of a congested network, the SUE traffic assignment algorithm provides a more realistic depiction of traffic flows (Easa, 1991; Lam and Lo, 2004). Within this algorithm, the process starts with an initial inter-zonal travel time matrix that corresponds with a free flow situation. This matrix is calculated with a shortest path algorithm that uses the free flow travel time on each link of the transportation network as impedance. Once an assignment is performed, congested travel time is calculated for each link using a link performance (delay) function that relates the link’s travel time to its congestion level (i.e. traffic volume to capacity ratio). The outcome is then used to calculate an inter-zonal travel time matrix that corresponds to a congested situation.

Since the trip distribution and modal split models are usually formulated as functions of congested inter-zonal travel time among other factors (Ortuzar and Willumsen, 2001; Hensher et al. 2005), the new travel time matrix from the traffic assignment routine is used to recalculate the trip matrices from the trip distribution and modal split submodels to generate a new pattern of O-D flows that are re-assigned to the network. This in turn will result in a new pattern of inter-zonal congested travel times. Iterations to calculate the trips with the trip distribution, modal split and traffic assignment submodels are repeated until all inter-zonal congested travel times stabilize. At this point, the four-stage model is at equilibrium and provides the number of total motorized trips on the links of the city’s transport network. These trips can then be translated into indicators of system performance such as the ratio of flow to capacity, which reflects the congestion level on the road network.

While the TAZ and network layers of an UTMS are spatial in nature, early development in UTMS was based on non-spatial computer programs. However, recent advancements
during the 1990s in computing and Geographic Information Systems (GIS) have revolutionized the development of spatial decision support tools to study and simulate urban transportation systems (Slavin, 2004). Processing speed and storage capabilities have increased at an exponential rate in the past decade. At the same time, new ideas in software engineering, such as object-oriented languages, have facilitated the maintenance and incremental development of simulation programs. The widespread use of GIS made it easier to organize and display large volumes of spatial data. GIS has also provided an excellent interface for planners to experiment and simulate scenarios without the need for advanced training in modeling and computer programming. In this respect, the UTMS extended its modeling capabilities and was integrated with a GIS to produce a GIS-T package, that is, a GIS package for Transportation purposes. An example of the latter is the TransCAD GIS-T program, which was first introduced in 1988 (Slavin, 2004).

Despite the rapid advances made in GIS during the past decade and a half, the development of GIS-based UTMS applications remained fairly limited. The majority of these applications adopted an encompassing framework, which extends the functionality of a core GIS-T via scripting or macro languages that are native to GIS software. This, however, requires the UTMS to be dependent on existing commercial GIS-T programs (e.g: TRANSCAD or EMME/2) even if it is only using some of the functionalities of that GIS-T. While the programming of trip generation, trip distribution and modal split models is fairly straightforward in most GIS packages, the need for a shortest path and SUE traffic assignment routines mounted the dependence on commercial GIS-T programs. However, this approach requires carrying around the overhead of a large GIS-T (Buliung et al., 2005). To avoid this, recent efforts in the development of GIS-based decision support systems have been focused on adopting a modular framework. The objective of such an approach is to produce a stand-alone program that have all the necessary GIS capabilities and which can be shared at a minimal cost. Therefore, a modular framework can lead to maximizing the usage of the developed system by practitioners and researchers.

A GIS-T application based on a modular framework links a set of systems together to fulfill the objective of utilizing specific functions such as mapping to visualize spatial information and graphical user interface (GUI) to define input to the system and summarize output after the simulations. An example of this is the utilization of several components from the ESRI MapObjects spatial software (ESRI, 1996) within the Visual C++ programming language to develop the IMPULATE integrated urban land use and transportation model (Buliung et al, 2005). The development of IMPACT is based on the modular framework proposed in Buliung et al (2005). Therefore, the system will re-use many of the GIS-T functionalities already develop and built for IMPULATE including: mapping functionalities, interactive scenario dialogue boxes, shortest path and traffic assignment routines and graphical output summaries. Such initiative is deemed cost-effective since it will result in a stand-alone system that can be widely used for research, teaching as well as city planning.
3. The IMPACT System
IMPACT is developed to quantify over time the potential ramifications of an expanding elderly population coupled with its increased automobile in urban areas. For demonstration purposes we apply the model to the Hamilton CMA in Canada. The devised modeling framework of IMPACT explicitly simulates the aging of population over time as well as the travel demand of elderly drivers that are 65 years or older. Figure 2 presents the general structure of the model, which consists of the following three interlinked modules: (1) demographic, (2) transportation and (3) environmental. The two layers representing the Hamilton CMA consist of a Traffic Analysis Zone (TAZ) layer that is based on the 1996 census tract divisions and road network layer that represents all major roads and highways in the CMA. IMPACT has 163 TAZs, 1542 links and 1183 nodes.

Figure 2 here

Aging of population is handled with a multiregional demographic model that forecasts the progression of population by age and sex at the municipal and TAZ levels. Municipal population is projected via Rogers’ multiregional demographic model (Rogers, 1995). Age and sex-specific vital statistics on fertility, mortality and inter-municipal migration are used to project the progression of the 1996 population in five-year increments. The projected municipal population is then allocated to TAZs within the municipality using TAZ utilities that are calibrated with a spatial aggregate multinomial logit (SAMNL) model. The latter has the advantage of estimating TAZ destination choice utilities and probabilities from aggregated (regional or municipal) revealed destination choices (Kanaroglou and Ferguson, 1996; Ferguson and Kanaroglou, 1997; Kanaroglou et al, 2007). This is a plausible approach when disaggregated (TAZ) revealed destination choice data, as in our case, are not available. The model uses destination choice information about municipality \( I \) selected by the migrant along with the characteristics of TAZ \( i \) within municipality \( I \) to calculate TAZ \( i \) destination choice probability \( P_{i,j,t} \), that is, the conditional probability of moving into TAZ \( i \) of region \( I \), given that one is moving from region \( J \) to \( I \). The estimated linear in parameter systematic utility function \( V_{i,t} \) reflects the level of attractiveness of TAZ \( i \) and is formulated as a function of a list of TAZ \( i \) characteristics that includes the number of new dwellings, average dwelling rent values, number of schools, and percentage of park and recreational land uses.

Following the approach in Kanaroglou et al (2007), the utilities of the SAMNL model were employed to devise a modeling framework that extends the Rogers multiregional demographic model and enables it to perform small area projections. The devised approach consolidates the municipal and TAZ levels of geography and assures consistency in the projected population at both levels. Accordingly, it can be shown that the population of TAZ \( i \) within municipality \( I \) who are \( x + 5 \) years old at time \( t + 1 \) can be modeled as follows:
\[ K_{i,j}^{(t+1)}(x + 5) = \sum_{j=1}^{M} P_{i,j} S_{jl}(x) K_j^{(t)}(x) + S_{il}^2(x) K_{i,l}^{(t)}(x) + (1 - S_{il}(x)) S_{il}(x) \sum_{k=1}^{L_i} K_{i,k,l}^{(t)}(x) P_{i,k,l} \]

\[ P_{i,j}^{(t)} = \exp \left( \frac{1}{\lambda^l} \sum_{j=1}^{J} \exp \left( \frac{V_{i,j}^{(t)}}{\lambda^l} \right) \right) \]

\[ S_{jl}^{(t)}(x) = P_i^{(t)}(J) \cdot \sum_{k=1}^{K} \exp \left( \lambda^l \ln \sum_{j=1}^{J} \exp \left( \frac{V_{i,j}^{(t)}}{\lambda^l} \right) \right) \]

\[ P_{i,k}^{(t)} = \frac{\sum_{i=1}^{I} P_{i,k}^{(t+1)}(x) F_i(x)}{\sum_{i=1}^{I} \sum_{x=\alpha}^{\beta-5} P_{i,k}^{(t+1)}(x) F_i(x)} \cdot K_{i,k,l}^{(t+1)}(x) \]

Where \( \alpha \) and \( \beta \) in Equation 2 is the first and last age of childbearing, respectively. \( K_{i,j}^{(t+1)}(x) \) is the projected number of females from childbearing age \( x \) in TAZ \( i \) at time \( t + 1 \) and \( F_i(x) \) is municipality \( I \)'s annual birthrate of women in different childbearing ages \( x \). \( K_{i,j}^{(t+1)}(0) \) is the number of projected newborn babies in municipality \( I \) at time \( t + 1 \). Further
information on the calculation of the latter can be found in Rogers (1995). Equation (2) 
distributes \( K'_{i}^{(r+1)}(0) \) to TAZs in municipality \( l \) based on the proportion of fertile women in 
those TAZs at time \( t + 1 \). A detailed description of the above demographic model and the 
associated model parameters can be found in Kanaroglou et al. (2007).

The transportation module is based on the four-stage model discussed in the previous 
section. The model assesses the travel behavior of two cohorts: total driving population 
(age > 15); and the adult driving population (age between 15 and 64). The difference in the 
output from the two cohorts will provide the contribution of the elderly driving 
population (age 65+). For this, eight trip generation, sixteen trip distribution and sixteen 
modal split models were estimated by trip purpose (work and non-work trips) and for the 
morning (6am – 9am), day (9am – 4pm), afternoon (4pm – 7pm) and night (7pm – 6 am) 
periods of a typical days (i.e. 2 cohorts × 2 trip purposes × 4 periods of the day). The 
modeling included non-work trips, since the elderly population is more prone to 
generating those types of trips.

Generated work and non-work trips are simulated with ordered probit models following 
an approach similar to the one proposed in Páez et al. (2006). The models are estimated 
with disaggregate travel data that were obtained from the 1996 Transportation Tomorrow 
Survey (TTS), which is a household travel survey housed at the University of Toronto, 
Canada. Since in the ordered probit models we use age as one of the covariates, eight 
models were calibrated instead of sixteen to account for work and non-work trips that are 
generated by individual travelers during the four periods of the day. Personal and 
household explanatory variables along with zonal attributes were used to formulate the 
trip generation models in order to predict the probability of generating 0, 1, 2 and 3 or 
more trips. The explanatory variables used in the specification of the models include a list 
of categorical variables that classify travelers according to five age cohorts \( x \), including 15 
– 19, 20 – 34, 35 – 50, 51 – 64 and 65+. The last age cohort corresponds to the elderly 
traveler population. Personal attributes were also categorized with a list of dummy 
variables to identify if the traveler is a female, holds a driving license, owns a vehicle, 
holds a transit pass, owns a vehicle and holds a transit pass, is full time employed, has free 
parking at work and is a blue collar employee. Household attributes were introduced to 
identify if the family for which the traveler belongs is single, a couple, a couple with 
children, a single parent or any other family class that does not correspond to the above 
four types. Finally, zonal attributes included the median income in the TAZ and the 
geographic location of the TAZ as inferred from the \( X \) and \( Y \) coordinates of the TAZ’s 
centroid. Details about estimated parameters of trip generation models can be found in 
Maoh and Behan (2007).

Using the estimated ordered probit probabilities, the generated trips from TAZ \( i \) for a 
specific purpose, \( w \) (i.e. work or non-work), are calculated as follows:
\[ T_{ij}^w = \sum_x \left[ K_{i,t}^{(x+1)}(x) \left( \sum_c P_{x,c/i} \left( \sum_n n \cdot \Pr_{x,c/i}(n^w) \right) \right) \right] \]  

... (3)

Where \( K_{i,t}^{(x+1)}(x) \) is the predicted population of age cohort \( x \) in TAZ \( i \) at time \( t+1 \), as in equation (1). \( P_{x,c/i} \) is the probability that a traveler from age cohort \( x \) in TAZ \( i \) will belong to socio-economic group \( c \). The latter corresponds to any socio-economic group from age cohort \( x \) that could be formed from the combination of all individual and household characteristics used in the specification of the ordered probit models. The 1996 TTS micro data were used to identify all feasible socio-economic groups and to calculate the above probability for each one of those groups by age cohort and TAZ. \( \Pr_{x,c/i}(n^w) \) is the ordered probit probability that a traveler from age cohort \( x \) and socio-economic group \( c \) in TAZ \( i \) will generate \( n \) trips for purpose \( w \), where \( n \) takes on values of 0, 1, 2 and 3. It should be noted however, that since very few non-work trips are generated during the morning period, \( n \) takes on values of 0 and 1 for this period. On the other hand, \( n \) takes on values of 0, 1, and 2 for work trips generated during the morning and day periods. However, since very few work trips are generated during the afternoon and night, \( n \) takes on the values of 0 and 1 for those two periods of the day.

The generated trips predicted by equation (3) are distributed over the TAZs of the CMA using a production-constrained gravity model. The distribution is simulated using information on the inter-zonal congested travel times and the level of attractiveness, \( A_j \), in destination TAZ \( j \) to generate an origin-destination (OD) trip matrix with elements \( T_{ij}^w \) that provide the number of trips of purpose \( w \) that start in TAZ \( i \) and end in TAZ \( j \). Following Ortuzar and Willumsen (2003), those trips are calculated as follows:

\[ T_{ij}^w = T_{ij}^w \cdot \frac{A_j \exp(-\beta t_{ij})}{\sum_k A_k \exp(-\beta t_{ik})} \]  

... (4)

For work trips, \( A_i \) is set to \( E_j^a \), which is the total number of jobs in TAZ \( j \). This is the classical way of modeling the attraction for work trips where more jobs in a TAZ will attract more work trips. On the other hand, for non work trips, \( A_i \) is set to \( P_j F_j^\theta \), where \( P_j \) reflects the total number of people who live in a destination TAZ \( j \) and \( F_j \) reflects the percentage of non-residential land use (namely: commercial, governmental and institutional land uses) in a destination TAZ \( j \). The use of a compound attractiveness measure was to enable the model to capture the effects of both non-shopping trips such as visiting family and friends (with \( P_j \)) and shopping trips (with \( F_j \)). \( t_{ij} \) is an element in the congested travel times matrix, which reflects the time in minutes that will take to travel from TAZ \( i \) to TAZ \( j \) in a congested situation. \( \alpha, \beta, \gamma \) and \( \theta \) are parameters that were estimated with the observed 1996 TTS data.

Purpose-specific origin-destination (OD) trip matrices produced by equation (4) are split by mode to determine the proportion of trips that are made by automobile among other modes. For this, mode choice models based on the multinomial logit model (MNL) were
estimated for three modes that included: auto-drive, auto-passenger and other modes including transit. Observations of individual travelers from the 1996 TTS data were used to estimate the modal split models. Personal and household explanatory variables along with zonal attributes were used to formulate the mode choice models. Personal attributes were categorized with a list of dummy variables to identify if the traveler is a female, holds a driving license, holds a transit pass, is employed full time, or is a full/part time student. Household attributes were also introduced to reflect the size of the family for which the traveler belongs and the number of cars owned by that family. Finally, a zonal variable was used to account for the cost of traveling in the choice utilities of the auto-drive and auto-passenger modes. For this, the variable \( c_{ij} = t_{ij} / d_{ij} \) was used, where \( t_{ij} \) is the in-vehicle congested travel time (in minutes) that it takes to travel from TAZ \( i \) to \( j \) and \( d_{ij} \) is the Euclidian distance from TAZ \( i \) to \( j \). This variable measures how onerous it is to drive in congestion for long distances (Anderson et al., 1994). Information about the parameter estimates of the modal split models can be found in Maoh and Behan (2007).

During simulations OD trip matrices for any mode \( m \) and for purpose \( w \) is calculated as follows:

\[
mT_{w}^{ij} = T_{w}^{ij} \cdot \sum_{c} P_{c/i} \cdot P_{m,w/i,jc}
\]

where \( P_{c/i} \) is the probability that a particular traveler in TAZ \( i \) will belong to socio-economic group \( c \). The latter corresponds to any socio-economic group that could be formed from the combination of all individual and household characteristics used in the specification of modal split utilities (Ben-Akiva and Lerman, 1985). As before, the 1996 TTS micro data were used to identify all feasible socio-economic groups and to calculate the above probability for each one of those groups by TAZ. The mode choice probability \( P_{m,w/i,jc} \) on the other hand, is the probability that a traveler in TAZ \( i \) who belongs to socio-economic category \( c \) will choose mode \( m \) to travel to TAZ \( j \) for purpose \( w \). The modal split probability takes the form:

\[
P_{m,w/i,jc} = \frac{\exp(V_{m,w/i,jc})}{\sum_{m' \in S_{ijc}} \exp(V_{m',w/i,jc})}
\]

And

\[
V_{m,w/i,jc} = \beta' X_{m,w/i,jc}
\]

Where \( V_{m,w/i,jc} \) is the systematic utility of mode \( m \) for a traveler from socio-economic group \( c \) who is traveling from TAZ \( i \) to \( j \) for purpose \( w \). \( S_{ijc} \) is the choice set of feasible modes for this traveler (i.e. auto-drive, auto-passenger and other modes including transit) and \( X_{m,w/i,jc} \) is a matrix of column vectors of explanatory variables characterizing mode \( m \) for a trip of purpose \( w \) between TAZ \( i \) and TAZ \( j \) and the traveler of category \( c \). Finally \( \beta \) is a column vector of parameters that are estimated from the 1996 TTS data.

To make the model sensitive to changes in demographics, we allow the probability \( P_{c/i} \) to be dependent on the output provided by the demographic module. For this, the
probability $P_{c/i}$ for base year $t$ and a given gender $g$ will be updated during simulations to accommodate the changes in demographics as provided by the demographic module for year $t + 1$. Let $^gK'_{c/i,t}$ be the population from socio-economic group $c$ identified by gender type $g$ in TAZ $i$ at time $t$ and $^gK_{i,t}$ be the total population of gender type $g$ in TAZ $i$. Given the predicted population, $^gK^{t+1}_{i,t}$, of gender type $g$ in TAZ $i$ at time $t + 1$, the probability $P_{c/i}$ used in equation (5) to simulation outcome for time $t + 1$ is calculated as follows:

$$P_{c/i} = \left( \frac{^gK^{t+1}_{i,t} + ^gK'_{c/i,t}}{^gK_{i,t} + ^gK'_{c/i,t}} \right) \left( \sum_g ^gK^{t+1}_{i,t} \right)^{-1} \quad \ldots (8)$$

For a given period of the day, a given cohort and trip purpose $w$, the transportation module initially executes equation (4) with a free flow inter-zonal travel time matrix to generate $T_{ij}^w$. It then uses those free-flow inter-zonal travel times to execute equation (5) in order to identify motorized trips $^{M}T_{ij}^w$ for trip purpose $w$. Purpose-specific motorized trips are then added to generate the total motorized trips $^{M}T_{ij} = \sum_w^{M}T_{ij}^w$ in the CMA. Those are then assigned to the network via the traffic assignment routine. The assignment is performed using a free flow travel times matrix to estimate a new set of travel times in a congested situation. Then, the trip distribution, modal split and traffic assignment sub-modules are run again with this new set of inter-zonal travel time values. The iterations are repeated until the travel costs stabilize. The results are link flows for the cohort under consideration. In our case, simulations are executed for the ‘adult’ and ‘all population’ cohorts. The difference in measures from those two cohorts represents the contribution of elderly drivers to the total flow on the network.

The environmental module uses link flows and average speeds from the traffic assignment to provide estimates for CO, HC, NOx, PM2.5 and PM10 pollutants on each link. It also generates the total energy consumed per link. Average link speed is calculated from the link congested travel time that the traffic assignment produces. Similar to the approach followed by Anderson et al. (1996), link emissions are estimated after matching the MOBILE6.2C emission factors to estimates of link average speed and adjusting by link volumes. Energy consumption, on the other hand, is calculated with a formula that relates the amount of fuel consumption (in liters) to the total flow and average congested speed on the link. The parameters of the fuel consumption model are the same as those employed in a study of transportation emissions and energy by the City of Toronto Planning and Development Department (Cheng and Stewart, 1992).

4. Development Environment & Outputs
The development of the devised system follows a modular approach that integrates components from different technologies. The mathematical component of the model,
which simulates the demographic changes, travel patterns and related transportation performance measures is programmed in C++. This includes the traffic assignment and shortest path submodules. As a result, the developed system is a stand-alone platform that does not rely on commercial GIS-T packages like TransCad or EMME/2 to perform the traffic assignment. The developed platform has endowed GIS-T capabilities through the use of GIS components from the MapObjects spatial software. In general, an advantage of MapObjects is its ability to enable developers to incorporate mapping and spatial data handling capabilities into visual applications (ESRI, 1996; Buliueng et al. 2005). Therefore, the user of the system can manipulate, manage and analyze spatial and non-spatial information using familiar GIS and windows controls through the application. Visual C++, on the other hand, provides a set of Graphical User Interface (GUI) dialogue boxes that makes the system user friendly and easy to use.

The integration of the two computing technologies (MapObjects and Visual C++) makes the developed system robust such that it allows users of IMPACT to devise scenarios interactively via maps and spreadsheets. The program creates a set of internal rules to store the elements of any defined scenario. Once a scenario is devised, the Visual C++ program applies the rules to the systems’ database and stores the information in a format acceptable by the C++ routines. When the user executes a scenario, Visual C++ executes calculations following the sequence of operation described in Figure 2. When the system converges, all the output information is updated in the system’s database. The output from simulating a scenario is accessible though an intuitive GIS-based or map-driven GUI. The interface consists of a number of standard windows and additional controls that are commonly found in desktop GIS software like ArcGIS 9.x. Users are able to view, query and manipulate spatial and attribute data interactively via an onscreen map. The interface is also provided with a scenario dialogue box (Figure 3) that enables the user to define rules pertaining to the scenario to be simulated. Users can select one or more periods of the day as part of the simulation as well as specifying the time horizon for which simulation will be running. In this version of the model, users can run simulation until the year 2051.

**Figure 3 here**

IMPACT allows the user to retrieve two types of outputs once a simulation is completed: (1) spatial output that reflects link and census tract based variables, as shown in Figures 4, 5 and 6, and (2) system wide aggregates that can be provided by cohort, period of the day and simulation period. The system provides an array of output statistics that could be used in the analysis of the simulated scenario, as shown in Figure 7. Furthermore, the model provides system wide demographic projections, namely population pyramids, which describe how the population ages and evolves over time (Figure 8). Finally, IMPACT produces charts depicting trends over time to allow the user to view the emergences of demographics, travel patterns, emissions and energy consumption trends for the simulated time periods. Figures 9 and 10 illustrate the change in population size for
adults and elderly as well as the amount of Vehicle Kilometers Traveled by the elderly in the Hamilton CMA between 1996 and 2051.

**Figures 4 – 10 here**

It is worth mentioning that all the graphical output from the system (e.g. Figures 5 to 10) can be exported in tabular format for further analysis. For instance, we exported the projected Vehicle Kilometers Traveled (VKT) and population size for a status quo scenario that ran from the year 2006 to 2051. The results, which are obtained for the adult (15 – 64) and elderly driver cohorts (65+) are summarized in Table 1. We also exported and summarized the number of work and non-work trips for the day period (9am – 4:00pm) for the adult and elderly drivers in Table 2. As can be seen, the model is predicting a steep increase in VKT and per capita VKT for elderly drivers over time. More specifically, VKT keep increasing until the year 2036, in tandem with the increase in the elderly driver population, especially for the day and afternoon periods. Those periods correspond to the time of the day when travel demand for the elderly drivers is at its peak. After 2036, VKT and per capita VKT start declining as the elderly drivers population starts declining but remain higher than the base year levels in 2006. In comparison to the travel pattern of the elderly, VKT and per capita VKT for the adult population declines over time parallel to the decline in the size of the adult population.

**Table 1 here**

**Table 2 here**

The results on VKT are rather interesting when combined with the trends observed in Table 2. The model predicts an increase in the number of day trips (work and non work) for the elderly in response to the increase in the number of elderly drivers. By comparison, the number of adult trips will decrease over time as the numbers of adult drivers decrease. The number of trips per capita for both cohorts remains virtually unchanged over time. However, VKT per capita does not follow this pattern and tend to increase for the elderly. This suggests that the increase in the number of elderly drivers will be associated with an increase in the level of elderly mobility over time.

The increase in elderly mobility is due to the growth in the number of elderly drivers as well as the change in the spatial distribution of population. The latter will increase the level of spatial interaction for the non-work trips that are generated by the elderly through the \( P_j^* \) variable in equation 4. The results in table 3 indicate that the \( \gamma \) parameter in the “all population” model is significantly larger than its counterpart in the “adult” model. The difference in the size of the parameter across the two models accounts for the elderly contribution on the generated non-work (social) trips between zones \( i \) and \( j \). Therefore, the increase in the number of elderly in the system due to population aging and the change in the spatial distribution of population over time will increase the level of spatial interaction for the non-work trips generated by the elderly. As a result, the level of traffic flow on
particular links of the transportation networks will increase leading to a substantial increase in VKT for the elderly as shown in Table 1. It should be noted that despite the increase in the size of the elderly population over time, adult trips and their associated VKT levels will continue to constitute the majority of the total trips and VKT in the study area. That is, the elderly will continue to make fewer trips when compared to the adult driving population but their travel demand will increase over time. Those observations are inline with the findings documented in Newbold et al (2005).

**Table 3 here**

5. Conclusion
This paper reported on the work undertaken to develop IMPACT, a GIS-based decision support tool (DST) that will be used to simulate the impact of elderly population on the transportation system in the Hamilton CMA. In recent years, advancements made in geomatics have revolutionized the development of spatial software. For instance, tools like MapObjects allow the development of efficient spatially oriented decision support systems by offering a wide range of functionalities to manipulate and analyze spatial data without the need to rely on commercial GIS platforms. An innovative and cost-effective approach has been adopted to develop IMPACT. We re-used many of the GIS and computing functionalities that were employed to develop the DST discussed in Buliung et al. (2005). The result is a stand-alone simulation model with an intuitive GIS-based graphical user interface that is built using MapObjects and Visual C++.

The developed tool will help us to conduct research that will advance our knowledge on the likely impacts of an expanding older population coupled with its increased automobility on the Hamilton’s CMA urban environment. The system also serves as a prototype that can be followed in studying similar demographic and transportation processes in other Canadian cities. Our preliminary analysis with the developed system indicate a consistent increase in the number of trips, VKT and the level of mobility of elderly drivers as a result of population aging over time. This appears to be more pronounced for day travel (9:00am – 4:00pm), which is the period when the elderly undertake most of their automobile traveling. The simulation results provide some insight about the future of travel in the study area. Therefore, the developed system can help planners and decision makers strengthen their future master plans by accounting for the travel demand of elderly in the years to come. Near future research with the developed system will focus on defining various demographic and transportation related scenarios that will be used to assess problems related to urban sustainability and the performance and usage of the transportation system.
Acknowledgment
This project was supported financially by grant DEC#SCO from GEOIDE (Geomatics for Informed Decisions), one of Canada’s Networks of Center of Excellence. The second author is grateful to the Canada Research Chairs program for financial support.
Figure 1: The Hamilton Census Metropolitan Area (CMA) in the regional context
Figure 2: General structure of IMPACT
Figure 3: Scenario dialogue box
**Figure 4:** List of spatial outputs for links and census tracts

### Spatial Outputs - Links

Select the simulation period and the variables for a given simulation that you wish to map on the Hamilton Links:

- **Simulation Period:** 1996-2001
- **Time of Day:** Morning
- **Cohorts:** All Population
- **Variable:**
  - Total Flows
  - Reverse Flows
  - Forward Flows
  - Uncongested NOx
  - Uncongested CO
  - Uncongested HC
  - Congested NOx
  - Congested CO
  - Congested HC
  - Congested Travel Times
  - Uncongested Average Speeds
  - Congested Average Speeds
  - Energy Consumption

### Spatial Outputs - Census Tracts

Select the simulation period and the variables for a given simulation that you wish to map on the Hamilton Links:

- **Simulation Period:** 1996-2001
- **Time of Day:** Morning
- **Cohorts:** All Population
- **Variable:**
  - Total Generated Work Trips
  - Total Generated Nonwork Trips
  - Total Generated Trips
  - Motorized Work Trips by Zone of Origin
  - Motorized Nonwork Trips by Zone of Origin
  - Total Motorized Trips by Zone of Origin
  - Motorized Work Trips by Zone of Destination
  - Motorized Nonwork Trips by Zone of Destination
  - Total Motorized Trips by Zone of Destination
  - Male Population
  - Female Population
Figure 5: Spatial output by census tract (e.g. total generated trips by elderly in the morning, 2031–2036)
Figure 6: Spatial output by link (e.g: total flow by all population, 2046 – 2051)
Figure 7: System Wide Summary Statistics
Figure 8: Population Pyramids, 2006 and 2036
Figure 9: Projected Population in the Hamilton CMA, 2001 – 2051
**Figure 10:** Vehicle Kilometers Traveled by the Elderly population in the morning, 2001 – 2051
Table 1: Projected VKT and per capita VKT for adult and elderly drivers cohorts, 2006 – 2051

<table>
<thead>
<tr>
<th>Period</th>
<th>Population</th>
<th>Morning</th>
<th>Day</th>
<th>Afternoon</th>
<th>Night</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adult</td>
<td>Elderly</td>
<td>Adult</td>
<td>Elderly</td>
<td>Adult</td>
</tr>
<tr>
<td>2006</td>
<td>572,933</td>
<td>109,735</td>
<td>370,455</td>
<td>3,767</td>
<td>72,114</td>
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<tr>
<td></td>
<td>(0.647)</td>
<td>(0.034)</td>
<td>(0.126)</td>
<td>(0.098)</td>
<td>(0.326)</td>
</tr>
<tr>
<td>2011</td>
<td>575,254</td>
<td>128,158</td>
<td>361,231</td>
<td>8,225</td>
<td>73,842</td>
</tr>
<tr>
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<td>(0.628)</td>
<td>(0.064)</td>
<td>(0.128)</td>
<td>(0.133)</td>
<td>(0.341)</td>
</tr>
<tr>
<td>2016</td>
<td>568,953</td>
<td>149,067</td>
<td>348,599</td>
<td>9,719</td>
<td>73,027</td>
</tr>
<tr>
<td></td>
<td>(0.613)</td>
<td>(0.065)</td>
<td>(0.128)</td>
<td>(0.145)</td>
<td>(0.345)</td>
</tr>
<tr>
<td>2021</td>
<td>557,701</td>
<td>171,910</td>
<td>329,777</td>
<td>13,340</td>
<td>70,875</td>
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<tr>
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<td>(0.591)</td>
<td>(0.078)</td>
<td>(0.127)</td>
<td>(0.155)</td>
<td>(0.348)</td>
</tr>
<tr>
<td>2026</td>
<td>538,716</td>
<td>199,385</td>
<td>317,414</td>
<td>15,517</td>
<td>68,933</td>
</tr>
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<td>(0.589)</td>
<td>(0.078)</td>
<td>(0.128)</td>
<td>(0.166)</td>
<td>(0.345)</td>
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<tr>
<td>2031</td>
<td>519,772</td>
<td>223,926</td>
<td>304,257</td>
<td>16,334</td>
<td>66,835</td>
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<td>(0.585)</td>
<td>(0.073)</td>
<td>(0.129)</td>
<td>(0.168)</td>
<td>(0.348)</td>
</tr>
<tr>
<td>2036</td>
<td>509,970</td>
<td>233,413</td>
<td>296,668</td>
<td>16,142</td>
<td>65,035</td>
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<td>(0.582)</td>
<td>(0.069)</td>
<td>(0.128)</td>
<td>(0.167)</td>
<td>(0.354)</td>
</tr>
<tr>
<td>2041</td>
<td>505,178</td>
<td>229,210</td>
<td>290,313</td>
<td>15,800</td>
<td>64,449</td>
</tr>
<tr>
<td></td>
<td>(0.575)</td>
<td>(0.069)</td>
<td>(0.128)</td>
<td>(0.164)</td>
<td>(0.359)</td>
</tr>
<tr>
<td>2046</td>
<td>498,902</td>
<td>222,979</td>
<td>283,818</td>
<td>14,626</td>
<td>63,543</td>
</tr>
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<td>(0.569)</td>
<td>(0.066)</td>
<td>(0.127)</td>
<td>(0.162)</td>
<td>(0.361)</td>
</tr>
<tr>
<td>2051</td>
<td>489,831</td>
<td>214,714</td>
<td>276,041</td>
<td>13,351</td>
<td>62,299</td>
</tr>
<tr>
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<td>(0.564)</td>
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<td>(0.127)</td>
<td>(0.161)</td>
<td>(0.363)</td>
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</tbody>
</table>

Note: Per capita VKT are the values in brackets.
Table 2: Predicted day trips (9 am – 4 pm) and per capita day trips for adults and elderly, 2006 – 2051

<table>
<thead>
<tr>
<th>Cohort</th>
<th>Trip Type</th>
<th>2006</th>
<th>2011</th>
<th>2016</th>
<th>2021</th>
<th>2026</th>
<th>2031</th>
<th>2036</th>
<th>2041</th>
<th>2046</th>
<th>2051</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Non-work</td>
<td>37,243</td>
<td>39,050</td>
<td>38,746</td>
<td>37,540</td>
<td>35,803</td>
<td>34,606</td>
<td>34,204</td>
<td>33,960</td>
<td>33,253</td>
<td>32,402</td>
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<tr>
<td></td>
<td></td>
<td>(0.065)</td>
<td>(0.068)</td>
<td>(0.068)</td>
<td>(0.067)</td>
<td>(0.066)</td>
<td>(0.067)</td>
<td>(0.067)</td>
<td>(0.067)</td>
<td>(0.067)</td>
<td>(0.066)</td>
</tr>
<tr>
<td>Adults</td>
<td>Work</td>
<td>8,008</td>
<td>7,760</td>
<td>7,501</td>
<td>7,277</td>
<td>7,118</td>
<td>6,949</td>
<td>6,805</td>
<td>6,677</td>
<td>6,607</td>
<td>6,536</td>
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<tr>
<td></td>
<td></td>
<td>(0.014)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.013)</td>
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</tr>
<tr>
<td></td>
<td>Total</td>
<td>45,251</td>
<td>46,810</td>
<td>46,247</td>
<td>44,817</td>
<td>42,921</td>
<td>41,555</td>
<td>41,009</td>
<td>39,860</td>
<td>38,938</td>
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<td></td>
<td></td>
<td>(0.079)</td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.080)</td>
<td>(0.080)</td>
<td>(0.080)</td>
<td>(0.080)</td>
<td>(0.080)</td>
<td>(0.080)</td>
<td>(0.079)</td>
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<tr>
<td></td>
<td>Non-work</td>
<td>11,757</td>
<td>16,242</td>
<td>19,049</td>
<td>22,130</td>
<td>25,585</td>
<td>28,038</td>
<td>28,515</td>
<td>27,800</td>
<td>26,997</td>
<td>26,047</td>
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<td></td>
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<td>(0.107)</td>
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<td>(0.128)</td>
<td>(0.129)</td>
<td>(0.128)</td>
<td>(0.125)</td>
<td>(0.122)</td>
<td>(0.121)</td>
<td>(0.121)</td>
<td>(0.121)</td>
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<tr>
<td>Elderly</td>
<td>Work</td>
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<td>385</td>
<td>458</td>
<td>532</td>
<td>609</td>
<td>660</td>
<td>664</td>
<td>639</td>
<td>614</td>
<td>588</td>
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<td>(0.003)</td>
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<tr>
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<td>Total</td>
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<td>16,627</td>
<td>19,507</td>
<td>22,662</td>
<td>26,194</td>
<td>28,698</td>
<td>29,179</td>
<td>28,439</td>
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<td>(0.132)</td>
<td>(0.131)</td>
<td>(0.128)</td>
<td>(0.125)</td>
<td>(0.124)</td>
<td>(0.124)</td>
<td>(0.124)</td>
</tr>
</tbody>
</table>

Note: Per capita trips are the values in brackets
### Table 3: Parameter estimates of work and non-work trip distribution models

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Adults</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Morning</td>
<td>Day</td>
<td>Afternoon</td>
<td>Night</td>
<td>Morning</td>
<td>Day</td>
<td>Afternoon</td>
<td>Night</td>
</tr>
<tr>
<td>α (Work)</td>
<td>0.09488</td>
<td>0.03349</td>
<td>0.00591</td>
<td>0.01285</td>
<td>0.09609</td>
<td>0.03436</td>
<td>0.00593</td>
<td>0.01307</td>
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<td>(17.69)</td>
<td>(9.43)</td>
<td>(3.44)</td>
<td>(6.42)</td>
<td>(17.82)</td>
<td>(9.57)</td>
<td>(3.45)</td>
<td>(6.48)</td>
<td></td>
</tr>
<tr>
<td>β (Work)</td>
<td>0.17840</td>
<td>0.10701</td>
<td>0.03416</td>
<td>0.01564</td>
<td>0.18074</td>
<td>0.10937</td>
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<td>(28.86)</td>
<td>(26.88)</td>
<td>(17.55)</td>
<td>(6.76)</td>
<td>(29.10)</td>
<td>(27.16)</td>
<td>(17.60)</td>
<td>(6.72)</td>
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<tr>
<td>γ (Non-work)</td>
<td>0.36630</td>
<td>1.16982</td>
<td>1.56452</td>
<td>1.32806</td>
<td>0.39292</td>
<td>1.27773</td>
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<td>1.39933</td>
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<td>(8.49)</td>
<td>(17.36)</td>
<td>(23.50)</td>
<td>(21.24)</td>
<td>(8.86)</td>
<td>(18.15)</td>
<td>(23.71)</td>
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</tr>
<tr>
<td>θ (Non-work)</td>
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<td>0.03550</td>
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<td>-0.06000</td>
<td>0.03188</td>
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<tr>
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<td>(-4.05)</td>
<td>(-5.47)</td>
<td>(4.10)</td>
<td>(3.58)</td>
<td>(-3.60)</td>
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<tr>
<td>β (Non-work)</td>
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<td>0.37765</td>
<td>0.38079</td>
<td>0.21400</td>
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<td>0.39347</td>
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<tr>
<td>(44.85)</td>
<td>(67.57)</td>
<td>(55.09)</td>
<td>(57.97)</td>
<td>(46.13)</td>
<td>(71.84)</td>
<td>(56.34)</td>
<td>(58.75)</td>
<td></td>
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</tbody>
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Note: Estimated parameters are provided in the table with t-stats in parentheses
IMPACT: An Integrated GIS-Based Model for Population Aging Consequences on Transportation
H. Maoh, P. Kanaroglou, D. Scott, A. Páez, B. Newbold

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ESRI (1996). Building Applications with MapObjects, Environmental Systems Research Institute, Redlands CA


