MOBILITY, ACCESSIBILITY AND ACTIVITY PARTICIPATION: A COMPARATIVE ASSESSMENT OF METHODS TO IDENTIFY RURAL TRANSPORT DISADVANTAGE

Md. Kamruzzaman, Built Environment Research Institute, University of Ulster, UK.
Kamruzzaman-M@email.ulster.ac.uk

Julian Hine, School of the Built Environment, University of Ulster, UK.
JP.Hine@email.ulster.ac.uk

ABSTRACT

Traditionally, transport disadvantage has been identified using accessibility analysis although the effectiveness of the accessibility planning approach to improving access to goods and services is not known. This paper undertakes a comparative assessment of measures of mobility, accessibility, and participation used to identify transport disadvantage using the concept of activity spaces. A 7 day activity-travel diary data for 157 individuals was collected from three case study areas located in rural Northern Ireland. A spatial analysis was conducted to select the case study areas using criteria derived from the literature. The criteria are related to the levels of area accessibility and area mobility which are known to influence the nature of transport disadvantage. Using the activity-travel diary data individuals weekly as well as day to day variations in activity-travel patterns were visualised. A model was developed using the ArcGIS ModelBuilder tool and was run to derive scores related to individual levels of mobility, accessibility, and participation in activities from the geo-visualisation. Using these scores a seven-factor ANOVA with a full factorial interaction between the factors was conducted using the general linear model (GLM) to identify patterns of transport disadvantage. This study found a positive association between mobility and accessibility. Despite a number of groups were identified as transport disadvantaged using the indicators of both mobility and accessibility in space and time, the levels of participation in activities of the identified groups did not vary significantly when compared to the advantaged groups. This suggests that participation in activities is a matter of survival in life. Policy interventions should therefore be directed in a way that these activities can be undertaken with relative ease through improving accessibility and mobility options.

Keywords: Accessibility; Mobility; Participation; GIS; Travel Behaviour; Transport Disadvantage.

1. INTRODUCTION

Lack of participation in activities has been identified as the key outcome of social exclusion (Burchardt et al., 1999; 2002; Shortall, 2008). Transport is seen to play a central role in this process as it enables people to reach essential opportunities in which they can participate (Currie and Stanley, 2008; Hine and Mitchell, 2001; 2003; Kenyon et al., 2002; SEU, 2003). Transport disadvantaged groups or individuals lack the ability to travel and participate in activities and become socially excluded (Stanley and Lucas, 2008). As a result, the identification and reduction of transport disadvantage is now an integral part of transport policy (DfT, 2006; Preston and Rajé, 2007; SEU, 2003; Wilson, 2006). Transport disadvantage has been defined as a situation where mobility impaired people live in an area with limited opportunities (Hurni, 2006; Stanley and Stanley, 2004). This means that transport disadvantage is a function of both access to transport and access to opportunities (e.g. job, shopping). The policy challenge therefore relates to the ability to identify those groups and individuals in society who face transport disadvantage; because both transport and opportunities remain unequal both within and between areas (Hine and Mitchell, 2003; Hodge et al., 2002; Knowles, 2006; Parkes and Thrift, 1980). As a result, the need to analyse disaggregated data to identify transport disadvantage has been highlighted (Hine and Grieco, 2003; Kamruzzaman et al., In Press).

Accessibility planning is now a key policy tool to reduce social exclusion within many local transport plans in the UK (Cass et al., 2005; Currie and Stanley, 2008; Farrington and Farrington, 2005). Despite its usefulness, studies have highlighted a number of weaknesses of this approach in identifying transport disadvantage. Methodology has been identified as one of these barriers, particularly where it has been unable to identify people's actual patterns of travel and participation in activities (DfT, 2006; Lucas, 2006). Stanley and Vella-Brodrick (2009) have indicated that there has been little attempt to go beyond accessibility planning and the effectiveness of accessibility planning to improve peoples ability to participation in activities is not known. Besides, this approach is too aggregate in nature to be able to identify the differential impacts of transport policies upon the disadvantaged groups (DfT, 2006). The weakness of such an approach is that transport-related social exclusion is not always a socially and spatially concentrated process (Hine and Grieco, 2003; Preston and Rajé, 2007).

Although transport disadvantage is a combined outcome of both a lack of access to transport and a lack of access to opportunities, traditionally used measures evaluate these two aspects separately (Casas, 2007). For instance, a number of studies have evaluated aspects of mobility by examining indicators such as car-ownership level; distance to public transport services (e.g. bus stops) etc. to identify transport disadvantaged groups/areas (see, Battellino et al., 2005; Cebollada, 2009; Currie et al., 2009; Hine and Mitchell, 2001; 2003; Wu and Hine, 2003). These approaches therefore ignore issues associated with accessibility to opportunities in which individuals can participate in without being too mobile if opportunities are available and within reach. Studies have shown that even a person with a high level of mobility (such as an able-bodied car driver) may have poor access to shops and services because of the residential location in which they live (Stanley and Stanley, 2004). In a similar way, accessibility based measures examine opportunities available within a certain travel distance from a zone (see, Church et al., 2000; DfT, 2006). This approach therefore ignores the differential levels of mobility of the individuals living in the same area (Farrington, 2007).

In order to overcome these weaknesses, researchers have recently adopted activity based approaches including the application of the activity space concept to the measurement of accessibility by taking into account individuals actual mobility levels and participation in activities. Activity spaces are the subset of all locations in which an individual has direct physical contact as a result of his/her day to day activity (Buliung et al., 2008; Golledge and Stimson, 1997; White, 1985). Activity spaces therefore shape an individual's territory and the opportunities available within this territory are generally considered to be those that the individual is aware of and potentially accessible to him/her (White, 1985). Researchers in different fields have attempted to capture the boundary of this territory to assess accessibility. Individual levels of movement and the opportunities that actually are reached within this territory are generally considered as their levels of mobility and participation in activities in this approach (Becker and Gerike, 2008; Verron, 2008).

Despite being effectively applied in different research contexts, several important issues have however been ignored while applying these indicators. Transport related social exclusion is not just due to the main effects of different causal factors such as car-ownership and income but rather the interactions between these different factors. The interactions between different causal factors need to be modelled in order to identify transport disadvantage. Previous research studies have modelled only the main effects of different explanatory factors without considering their interactions in identifying transport disadvantage. Transport disadvantage is a relative concept and needs to be considered in the wider context of activities of others living in the same area (Jain and Guiver, 2001; Stanley and Vella-Brodrick, 2009). For instance, a lower level of accessibility for an individual living in a rural area does not necessarily mean that the individual is transport disadvantaged when compared to an individual living in an urban area. Besides, the different measures using the concept of activity spaces have traditionally not incorporated the type of opportunities available as well as the type of activities participated in. An evaluation of the nature of available opportunities and participation is helpful because a lack of existence of any type of opportunities (or a lack of participation in any type of activities) is sufficient for social exclusion to exist (Burchardt et al., 2002). In addition, studies have shown that both access to transport and access to opportunities vary over time (e.g. peak hours vs. off-peak hours, weekdays vs. weekends) (Kwan and Weber, 2008; Weber and Kwan, 2003; Wu and Hine, 2003). This means that an individual who is not disadvantaged in a certain period of time is certainly at risk of being excluded at another period of time. Very little attempt has been made to capture these dynamics using the activity space concept to identify transport disadvantage.

Based on the above discussion, the objective of this research is twofold: firstly, to assess the impacts of accessibility and mobility on individual levels of participation in activities; secondly, to identify the patterns of transport disadvantage in space and time using disaggregated measures of mobility, accessibility, and participation in activities by incorporating the relativity concept. Section 2 reviews the development of activity space concept to the measurement of accessibility, mobility, and participation in activities. Section 3 discusses the development of the methodology that was used in identifying transport disadvantage in this research. Section 4 portrays the findings of the applied measures. The policy implications of these findings are discussed in Section 5 with special reference to the context in which this research is based.

2. LITERATURE REVIEW

Different methods of deriving the boundary of activity spaces have been proposed in the literature including standard distance circle (SDC) (Buliung and Kanaroglou, 2006b; McCray and Brais, 2007), standard deviational ellipse (SDE) (Buliung and Kanaroglou, 2006b; Newsome et al., 1998; Schönfelder and Axhausen, 2003), minimum convex polygon (MCP) (Buliung and Kanaroglou, 2006b), polygonal generalised travel area (Rogalsky, In Press), buffering along travelled routes (Schönfelder and Axhausen, 2003), and area generated by using the longest distance activity (LDA) location from the home (Casas, 2007; Casas et al., 2009). Buliung and Kanaroglou (2006b) have generated a standard distance circle (SDC) using standard distance (SD) of activity locations as radius centred on mean centre. Using the SDC measure, they have shown that the size of activity spaces for sub-urban households are more dispersed than urban households. A similar method has been used by McCray and Brais (2007). This found that women who own cars have a greater size of activity spaces than non car owners. They have also reported that home location from transit route influenced the size of the SDC for the non-car user. Although the SDC suggests a dispersed or clustered pattern of activity spaces with a measure of areal extent, it cannot be used to investigate orientation or shape of the activity spaces (Buliung and Kanaroglou, 2006a). Buliung and Remmel (2008) indicate that individual activity spaces are likely to possess these properties due to heterogeneity in the spatial and spatio-temporal distribution of activity destinations, and the spatial structure of road networks.

Standard deviational ellipse (SDE) provides a unique approach to getting around this problem. It graphically represents the shape and direction of activity spaces on the one hand. On the other hand, the area of the ellipse represents the spatial extent of the activity spaces (Newsome et al., 1998). Ellipse based measures have been used to compare the dispersion between travellers (Buliung et al., 2008). Since the SDE is centred on a single point (the mean centre or any exogenously defined centre of gravity), much of the area inside an ellipse contains no activity points (Buliung and Remmel, 2008). Schönfelder and Axhausen (2003) have overcome the problem by creating and merging two ellipses centred on two pegs (e.g. home and office). However, the elliptical shape has been lost after merging the ellipses. Newsome et al. (1998) have proposed a practical approach to overcome this problem. Instead of drawing two ellipses, they have drawn a single ellipse using the distance of the furthest activity location among the discretionary activities from the foci of the ellipse. The foci represent the pegs (e.g. home, work). Therefore, all other activities remain within the ellipse. The ellipse then represents an inner limit of potential opportunities over which an individual is able to engage in activities. They have quantified their ellipse construct in two ways. Firstly, the ratio of the minor to major axis indicates the fullness of the ellipse representing the relative extent to which the traveller is willing, able, or required to deviate from the main travel route. Secondly, the area of the ellipse represents the size of the activity spaces. They have linked the outcomes of these measures with travellers' characteristics and found potentially useful in understanding travel behaviour.

MCP based measure has recently been introduced into travel behaviour research (Buliung and Kanaroglou, 2006a; 2006b). It was first introduced in the ecology literature in the late 1940s as an approach for measuring animal home-range (Mohr, 1947). With respect to human travel behaviour, the MCP is the smallest convex polygon containing all activity locations of an individual (Buliung et al., 2008). It provides a basic measure of the area or maximal geographical extent of the activity space on the one hand. Visually, on the other hand, the MCP provides a generalised depiction of the shape of activity spaces. Buliung et al. (2008) have mentioned that the MCP is a supplementary measure of traditional area based measures (e.g. ellipses), and have used the measure to explore weekday-to-weekend and day-to-day variation of travel behaviour. Using the MCP measure, Buliung and Kanaroglou (2006b) have shown that the size of activity spaces varies between CBD-based households and sub-urban households. Using a similar concept, Rogalsky (In Press) has created a polygonal generalised travel area using the origins and destinations of all trips for working, poor, single mother living in Knoxville. This work found that individuals with mobility constraints had smaller sized of activity spaces than others.

Schönfelder and Axhausen (2003) have mentioned that deriving activity space size in this way is a simplification of human behaviour and an overestimate of the potential knowledge of activity locations. In reality, there could be locations within this area that are either inaccessible due to mobility constraint (e.g. a lack of bus routes for non-car owning individuals) or travellers would intentionally avoid due to ethnic reasons (Wu and Hine, 2003). Golledge (1999) has proposed an alternative measure mentioning that transport network structures shape the travellers' perception of potential activity locations as well as the knowledge of place and the spatial orientation. Using this alternative concept, Schönfelder and Axhausen (2003) have measured activity space size by generating a 200m buffer distance along the shortest path routes between origins and destinations.

The area (size) of activity spaces using the different measures discussed above has traditionally been used as an indicator of individual accessibility. As a continuous geometric space the area (size) generated by these measures is larger than the space in which activities are consumed and participated in. Miller (1991) has mentioned that a large part of this area is useless for travel and activity participation because travel occurs along streets and activities occur at specific locations. As a result, he has discarded the planar form of the activity spaces and adopted only those discrete locations where activity could take place (e.g. street, buildings). After Miller (1991), the network-based approach has widely been adopted to measure individual accessibility (Kim and Kwan, 2003; Kwan, 1998; 1999; Kwan and Hong, 1998; Kwan and Weber, 2008; Miller, 1999; Weber and Kwan, 2002; Yu and Shaw, 2008). In relation to identifying transport disadvantage, Casas (2007) and Casas et al. (2009) have calculated distances from home to all destinations using a single weekday travel diary. The longest distance has been used as an indicator of mobility that delimits the size of activity spaces for an individual. This work has adopted a cumulative opportunity (accessibility) measure and counted the total number of opportunities available for an individual within the area generated, using the longest travel distance centred around the home placed over the network. The total number of opportunities has been used as an index of exclusion and has found a significant difference between the different groups (e.g. disabled, children).

Using the activity space concept to measure mobility, Schönfelder (2001) has used total distance travelled by an individual as an indicator of mobility. This work found that the amount of travel is influenced by the occupational characteristics of travellers on the one hand, and on the other hand, that the mobility also varies over time. Unlike Schönfelder (2001), Buliung and Kanaroglou (2006b) have used total daily household kilometres travelled (DHKT) as an indicator of household mobility. They have used Euclidean distance between successive activities to measure the DHKT and found that the DHKT varies with household structure (number of employed householders). The DHKT does not take into account the underlying friction (e.g. travel time, congestion) of travelling over the network. As a result, network based distance has been adopted as an indicator of mobility. Wyllie and Smith (1996) have reported that the mean travel distance for discretionary activities is higher for female than male extroverts. Kawase (1999) has used mean travel distance (expressed in minutes) to measure the size of commuting mobility in a suburb of Tokyo. This work has found that the commuting distance is shorter for married women than married men and the mobility is relatively stable over time for married women who are in higher paid jobs. Kamruzzaman et al. (In Press) have used average daily distance travelled as a measure of student mobility and found that students who live outside of the limits of a demand responsive service have a significantly higher level of mobility.

Although the number of trips is frequently used as an indicator of participation in society, Schönfelder and Axhausen (2003) have mentioned that much of the individuals trips are associated with one or few locations and can act only as a proxy measure. As a result, the number of unique activity locations visited by an individual has been used as an indicator of participation in activities (Kamruzzaman et al., In Press; Schönfelder and Axhausen, 2003). Wyllie and Smith (1996) have found a positive correlation between the level of extroversion and the number of activity sites visited by adolescents (female aged 13-16 and male aged 14-16). They have also used the total number of trips per person per week to activity sites as an indicator of participation and found a positive effect to the level of extroversion. Rollinson (1991) has adapted the definition of everyday geography provided by Seamon (1979, p.16) as 'the sum total of a person's first-hand involvements with the geographical world in which he or she typically lives' as a measure of participation in society. This study counted the number of places visited by elderly tenants living in single-room-occupancy hotels and concluded that the everyday geography of elderly men and women is highly constrained due to poverty and the barriers imposed on them by their neighbourhood environment e.g. street crime. Goldhaber and Schnell (2007) have studied the relationship between ethnicity and the level of segregation using the concept of activity spaces. They have derived a ratio of visited activities to the total number of activity locations present in a region as an index of participation.

3. DATA AND METHODS

3.1 Data collection

Data were collected from both primary and secondary sources for this research. Three case study areas were selected to collect primary data using criteria derived from the literature

(Table 1). The criteria are related to the relative accessibility to opportunities (close to urban area, self-contained village) and relative mobility options (close to motorway, close to train station) which determine the degree of disadvantage in rural areas (Cloke et al., 1994; Gray, 2000; Higgs and White, 2000; Nutley, 1985). A self-contained village is referred to as villages that contain the basic service facilities (e.g. post office, grocery, GP, pharmacy). Four criteria maps were prepared using Table 1 and were used to identify the three case study areas from rural Northern Ireland (Figure 1). Each criterion map satisfied only one criterion for a specific case and required further processing to satisfy all the criteria (e.g. a rural area which is close to the motorway may also be located close to an urban area). As a result, conditional operations (e.g., Intersect, Union, Erase) were conducted using these four criteria maps. From this analysis, Moira, Saintfield, and Doagh were identified as case study area 1, case study area 2, and case study area 3 respectively (Figure 2).

Table 1: Criteria for the selection of case study areas

Case study areas	Criteria: related to mobility		Criteria: related to accessibility	
	Close to motorway	Close to train station	A self-contained village	Close to urban area
Case study area 1	√	√	√	×
Case study area 2	×	×	√	×
Case study area 3	×	×	×	√

Figure 2a shows the location of the selected case study areas in their wider geographic context. Although both Moira and Saintfield are self-contained village and are located away from urban areas, Figure 2b and 2c show that the M1 motorway and the Moira train station are located within a short network distance of Moira whereas the closest train station and motorway are located more than 10km away from Saintfield. Doagh, on the other hand, has fewer local services and is located near to larger sized settlements such as Ballyclare, Glengormley, and Antrim (Figure 2d). The closest train station (Mossley west) is located more than 10km away from Doagh. The M2 motorway also passes more than 5km away from Doagh. The closest urban centres from Moira are Lurgan and Lisburn whereas the closest urban centres from Saintfield are Ballynahinch and Carryduff. However, these urban centres are located around 10km away from these case study areas (Moira and Saintfield). Despite the fact that the motorway is not located near to either Saintfield or Doagh, no differences were found to exist in terms of rural public (bus) transport services amongst the different case study areas. All the three case study areas were found to be located along inter-urban Ulster Bus routes (Moira: Lisburn-Lurgan route, Saintfield: Belfast-Downpatrick route, and Doagh: Belfast-Ballyclare route) with similar level of service frequency. Therefore, the area mobility differences amongst the case study areas remain only in terms of access to train services.

A total of 157 activity-travel diaries were collected for individuals from the selected three cases (45 diaries from Moira, 62 diaries from Saintfield, and 50 diaries from Doagh). These diaries contain seven days of consecutive out of home activity and the travel details of the respondents. An activity-travel diary form was designed and delivered to respondents with a postage paid return envelope. Instructions were provided to participants with the diary form on the coding and completion of their diary. A coding list of 29 trip purposes and 8 modes were provided to the respondents to choose from (Table 2). Respondents were instructed to consider every purposeful stop as a single trip during their journey. They were also instructed not to fill in the form for a particular diary day if they did not leave home on that day. Respondents were requested to fill in for each trip the following information: left at (time), left from (address), to go to (address), got there at (time), trip purpose, transport mode, and route/roads travelled. Respondents returned back the diary to the researchers address (pre-printed on the provided envelope) upon completion of their diary.

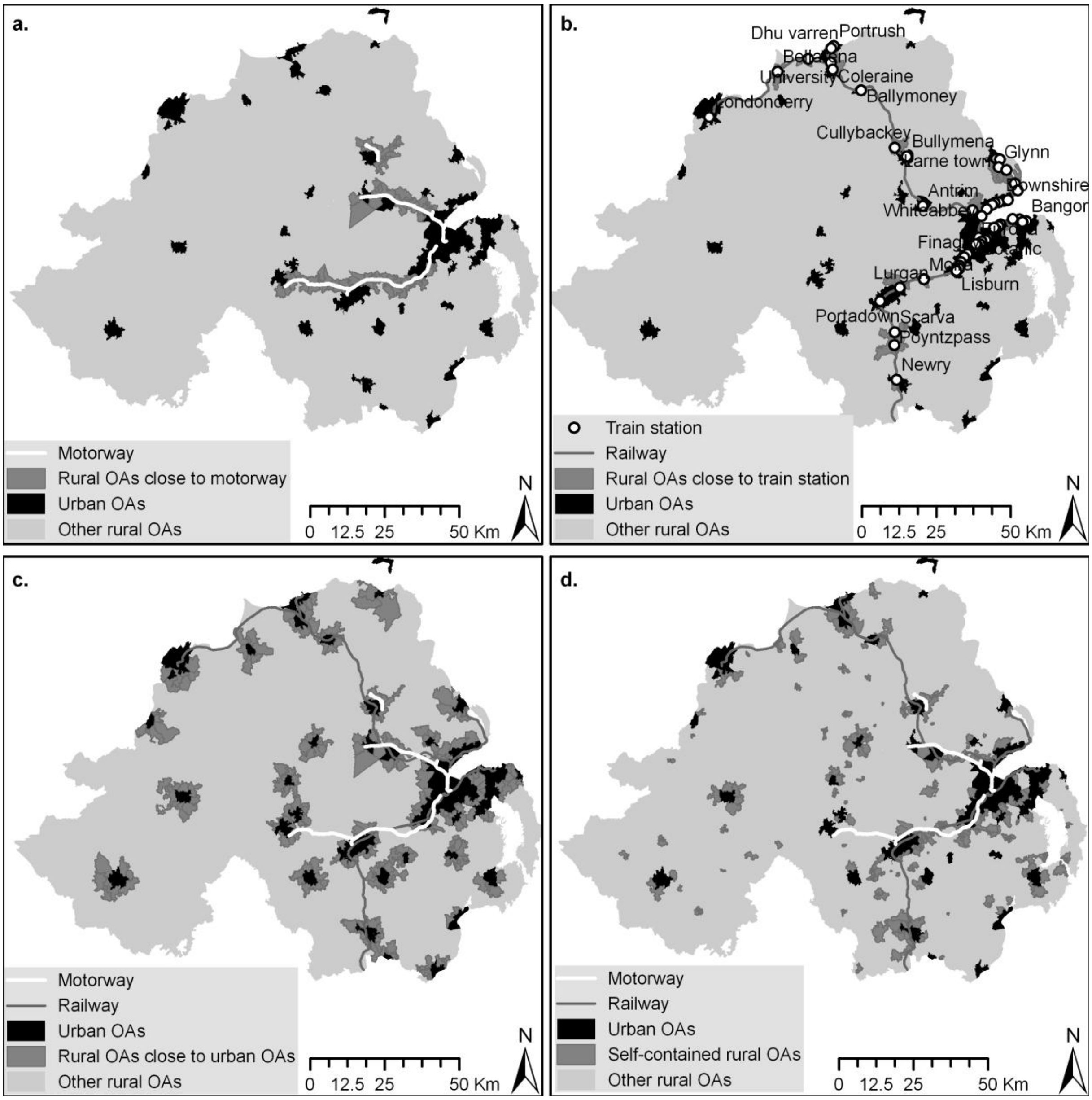


Figure 1: Criteria maps used for the selection of case study areas; a) rural areas close to motorway, b) rural areas close to train station, c) rural areas close to urban areas, and d) self-contained rural areas

Examination of previous research studies that have been conducted using travel diary data do not provide any clear evidence on the sample sizes required for this type of travel diary. Considering the number of diaries and diary days that have been reported in other research on this subject, the 157 diaries with 7 diary days were found to be representative of previous studies (see, Table 3). In addition to the collection of respondents' activity-travel data, their socio-economic data were also collected to use as explanatory variables in this research (Table 4). These explanatory variables included their gender, car-ownership status, level of income, home-ownership status, age, and occupational status. In order to address the relativity criteria (contextual differences), respondents' living area profile (criteria used for the selection of case study areas) was also used as a spatial explanatory variable in addition to the above six socio-economic variables (Páez, 2006). The spatial datasets that were used in this research were collected from the School of the Built Environment at the University of the Ulster (secondary source). The spatial extent of these datasets covers entire Northern Ireland. Data types (geometry) and important attributes of these datasets are shown in Table 5.

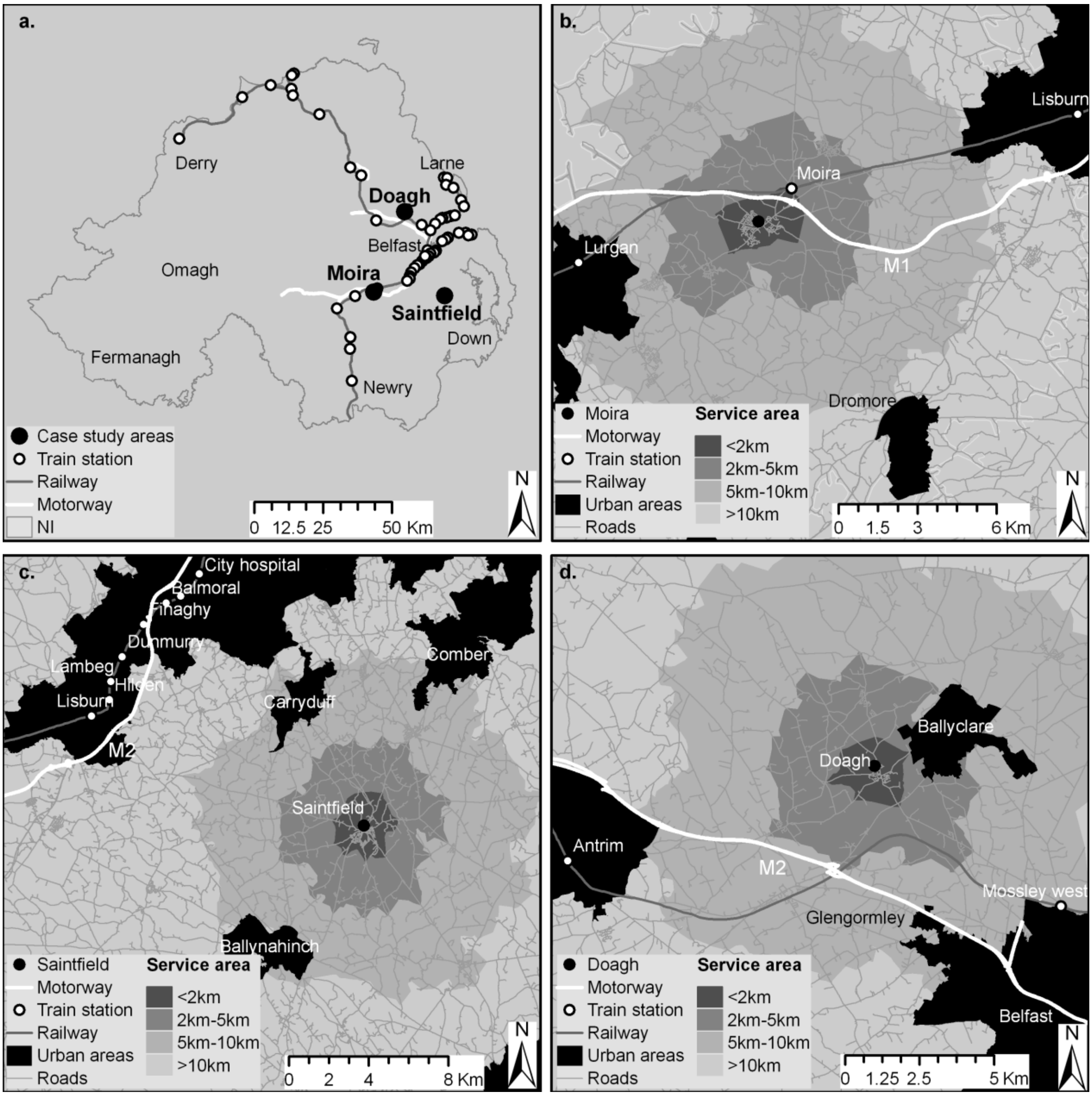


Figure 2: Location of the case study areas in terms of the differential levels of area accessibility and area mobility

Table 2: List of trip purposes and travel modes

Trip purposes		Travel mode
Main category	Sub-category	
Work	Any type of paid/voluntary work	Driving car
	Farming/Business	Lift (passenger in a car)
Social	Visiting friends and family	Bus
	Religious	Train
	Social networking/community/club	Taxi
Recreation	Amusement	Motorcycle
	Exercise	Bicycle
	Sports	Walk
Shopping	Shopping grocery	
	Shopping food	
	Other shopping (e.g. dress)	
Health	Visiting GP	
	Visiting dentist	
	Visiting hospital and clinic	
	Visiting pharmacy to get medicine	
Food	Hotel and restaurant	
	Bar	
Returning home	Travelling by a single mode (e.g. car, walk) to go home	
	Inter-modal changes to go home (e.g. bus-train)	
	Intra-modal changes to go home (e.g. bus-bus)	
Other	To drop off	
	To be dropped off	
	To pick up	
	To be picked up	
	To get bus/taxi/train	
	To get petrol	
	To fix car	
	To post items	
	To withdraw cash	

Table 3: Sample characteristics of several well known travel diary surveys

Citation	Context	Sample population	Number of diaries	Duration
Hine and Mitchell (2001)	Scotland	Non-car owning households	19	1 day
Rajé et al. (2003)	Bristol, England	General travellers	66	1 day
Rajé et al. (2003)	Nottingham, England	General travellers	71	1 day
Casas (2007)	New York, USA	Disabled and non-disabled	111 (each group)	1 day
Casas et al. (2009)	Erie and Niagara, USA	Children	674	1 day
Kamruzzaman et al. (In Press)	Northern Ireland	Student	130	2 days
Rogalsky (In Press)	Knoxville, USA	Single mother	19	1-5 days
Schönfelder and Axhausen (2003)	Halle and Karlsruhe, Germany	General travellers	300	6 weeks

Table 4: Socio-economic status of the respondents who participated in the activity-travel diary survey

Variables	Classification	Case study areas			Overall
		Moira	Saintfield	Doagh	
Gender	Male	40	47	48	45.2
	Female	60	53	52	54.8
Age	Young	53	73	52	60.5
	Older	47	27	48	39.5
Occupation	Working	62	57	56	58.0
	Non-working	38	43	44	42.0
Car-ownership	Non-car owning	16	18	12	15.3
	Car-owning	84	82	88	84.7
Home-ownership	Owner	71	73	84	75.8
	Rented	29	27	16	24.2
Income	Low income	67	48	56	56.1
	High income	33	52	44	43.9
		N=45	N=62	N=50	N=157

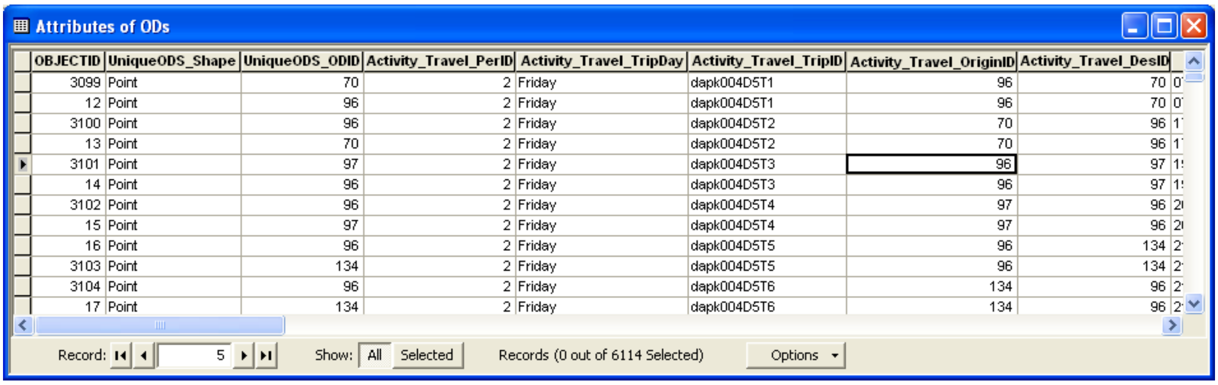
Table 5: Characteristics of spatial datasets collected from secondary sources

Name of the dataset	Data type	Important attributes
Output area (OA) boundary	Polygon	OA names, OA code, SOA code, LGD code, population weighted X and Y coordinates
Building footprint	Polygon	Type of building (e.g. residential, commercial)
Road centre line	Polyline	Road names, road class (e.g. motorway, A-class)
Railway centre line	Polyline	-
Train station	Point	Station name
Pointer address	Point (representing every building)	House number, street names, post code

3.2 Data processing

The 157 activity-travel diaries contained data on 3061 individual trips of which two return trips were to a destination in the Republic of Ireland (RoI). These four trips were excluded from the analysis. As a result, the remaining 3057 trips were processed for the purposes of this research. A database table was prepared in SPSS using the attributes associated with each trip. These attributes included person ID (identity), trip ID, trip day (e.g. Monday), trip origin address, origin ID, trip destination address, destination ID, trip start time, trip end time, travel mode, trip purpose, and travel time. A summary table was prepared using the entered addresses associated with both origins and destinations and it was found that the 3057 individual trips were associated with 459 unique addresses. These 459 unique activity locations (origins and destinations – OD) were extracted from the pointer address feature class and was referred to as unique OD feature class. Each unique location was assigned a unique identity number (OD ID) and these OD ID values were inserted into the corresponding origin ID and destination ID fields of the activity-travel database. The travel time of each trip was calculated by subtracting the trip start time from trip end time. Out of the 459 unique activity locations, 153 represented home locations. These home locations were extracted and referred to as the home feature class. This number (153) is less than the number of individuals (157) who provided diary because 3 individuals were living in the three different flats of a building in Moira. This building was represented by a single point in the pointer address database. On the other hand, both husband and wife of two households (one from Moira, and one from Saintfield) provided diaries.

The unique OD feature class was used to geo-reference the origin and destination of each trip of the activity-travel database using the Make Query Table tool in ArcGIS. The generated new feature classes were referred to as origins and destinations respectively. The OD ID attribute from the unique OD feature class and all attributes from the activity-travel database were accumulated to each of these new feature classes during the geo-referencing process (Figure 3). The destinations feature class was then appended to the origins feature class and referred to as an OD feature class. As a result, the total number of objects (records) in this OD feature class was doubled (6114 = 3057*2) in which one point (OD ID) geographically represents the origin and the other point (OD ID) geographically represents the destination of each trip (Figure 3). The trip ID values of this feature class were used to then identify and extract the origin and destination associated with each trip. From this feature class, the person ID and trip day attributes were used to make query and to visualise individuals spatio-temporal patterns of visited activity locations. The 29 sub-categories of trip purposes were grouped into 8 main categories: work, social, shopping, recreational, health, food, returning home, and other (Table 2).


Attributes of ODs

OBJECTID	UniqueODS_Shape	UniqueODS_ODID	Activity_Travel_PerID	Activity_Travel_TripDay	Activity_Travel_TripID	Activity_Travel_OriginID	Activity_Travel_DesID
3099	Point	70	2	Friday	dapk004D5T1	96	70
12	Point	96	2	Friday	dapk004D5T1	96	70
3100	Point	96	2	Friday	dapk004D5T2	70	96
13	Point	70	2	Friday	dapk004D5T2	70	96
3101	Point	97	2	Friday	dapk004D5T3	96	97
14	Point	96	2	Friday	dapk004D5T3	96	97
3102	Point	96	2	Friday	dapk004D5T4	97	96
15	Point	97	2	Friday	dapk004D5T4	97	96
16	Point	96	2	Friday	dapk004D5T5	96	134
3103	Point	134	2	Friday	dapk004D5T5	96	134
3104	Point	96	2	Friday	dapk004D5T6	134	96
17	Point	134	2	Friday	dapk004D5T6	134	96

Record: 5 Show: All Selected Records (0 out of 6114 Selected) Options

Figure 3: Geo-referencing of the origin and destination associated with each trip

The road centre line feature class was converted into a network dataset using distance (in metres) as a measure of network impedance. The road network dataset was used to generate routes for each trip using the ArcGIS Network Analyst tool. Instead of generating the shortest path route between the origin and destination of each trip, the travelled road names that were reported by the respondents were used as intermediate stop points to generate these routes. All the individual routes were appended to an empty feature class called all routes. The attributes associated with each trip from the activity-travel database were joined to the all routes feature class using trip ID as common fields.

Using the explanatory data from the respondents in the survey a database table, referred to as the explanatory database, was prepared in SPSS. A person ID (identity) variable was created and assigned to these variables. The person ID from the explanatory database matches the corresponding person ID as entered in the activity-travel database. Since the explanatory variables are nominal categories (e.g. gender: male and female) with more than two categories in the area profile variable (Moira, Saintfield, and Doagh), as a result, the contingency coefficients were derived to investigate the association amongst the explanatory variables (Table 6). The contingency coefficient measures an association between two categorical variables based on chi-square. The coefficient value ranges between 0 and 1, with 0 indicating no association between the row and column variables and values close to 1 indicating a high degree of association between the variables. Although Table 6 shows that a number of explanatory variables are significantly associated with each other, these associations are, however, relatively weak. The only strong association was found to exist between age and occupational status variables (0.447). Cross tabulation of these variables reveals that older people were mostly of non-working occupational status. As a result, this association was taken into account while interpreting the findings of this research.

Table 6: Correlations between the different explanatory variables

	Area profile	Gender	Age	Occupation	Car-ownership	Home-ownership	Income
Area profile	-	0.067	0.196[a]	0.055	0.067	0.131	0.148
Gender		-	0.179[a]	0.107	0.136	0.095	0.046
Age			-	0.447[a]	0.055	0.061	0.212[a]
Occupation				-	0.273[a]	0.120	0.228[a]
Car-ownership					-	0.285[a]	0.227[a]
Home-ownership						-	0.139
Income							-

[a] Correlation is significant at the 0.05 level (2-sided).

The building footprint feature class spatially represents different types of buildings in Northern Ireland and were considered as locations of opportunities where activities could take place. As a result, this feature class was used to calculate individual levels of accessibility in this research. The building type attribute of the building footprint feature class was reclassified as shown in Table 7. Originally the buildings were classified into 16 categories; these were reclassified into seven main categories (residential, commercial, industrial, recreational, social, admin and service, and other). This reclassification was made in a way that it matches, to a greater extent, to the main activity categories (Table 2). This was done in this manner with an intention to make a comparison between the types of opportunities available and the types of activities participated in, in the later stage of the analysis. However, this classification is indicative only rather than mutually exclusive. This is due to the fact that one building can perform different functions for different individuals. For instance, a shopping centre not only provides shopping opportunities to the individuals but also facilitates employment opportunities to many of them. Traditionally, accessibility has been calculated based on non-residential features (Kwan and Weber, 2008; Ortúzar and Willumsen, 1990). As a result, the non-residential buildings (other than residential buildings in the reclassified attribute) were extracted to assess individual levels of accessibility and was referred to as a non-residential feature class.

Table 7: Reclassification of the building type attribute used to assess individual levels of accessibility

Original classification	Reclassification	Number	Total area (m^2)
Dwelling houses	Residential	757753	57882509.4
Other general buildings e.g., garages		592075	49383928.3
Commercial buildings	Commercial	41558	10119147.5
Industrial buildings	Industrial	10761	7536451.6
Government administrative	Admin and services	1474	492600.4
Public services buildings		5813	641058.8
Law and administrative services buildings		95	43318.1
Buildings associated with health services		3597	1235298.9
Educational buildings		9682	3566286.2
Recreational buildings	Recreational	2583	751927.8
Antiquity buildings		25	1100.4
Glass buildings		9441	409782.2
Communal buildings	Social	5833	1346756.7
Religious buildings		4195	1096740.184
Building furniture e.g., elevators	Other	3143	174607.3
Other type of buildings		3	88.2
Total		1448031	134681601.9

3.3 Deriving indicators of mobility, participation, and accessibility

Individual levels of mobility, accessibility, and participation in activities were derived in this research using the concept of activity spaces. The methods that were adopted to calculate these indicators are discussed in the following sub-sections:

3.3.1 Mobility based measures

Mobility refers to an individuals ability to move (Moseley, 1979). Although car-ownership has frequently been used to refer to this ability, studies have shown that car-ownership does not always reflect actual mobility patterns of individuals particularly in rural areas because in rural areas it happens that individuals are forced to own a car (McDonagh, 2006). For instance, Currie et al. (2009) have found that forced car ownership households make fewer trips and travel shorter distances than their counterparts in outer Melbourne. As a result, individual travel distances were used as indicators of mobility in this research. The all routes feature class contains travel distance and travel time for each trip. Using these attributes a summary table was prepared based on person ID field to derive scores related to weekly total distance travelled and weekly total travel time per person. Since the total distance travelled and total travel time are measures of travel over the same network, these indicators do not exhibit an individual's actual geographical exposure. As a result, the all routes feature class was dissolved using the person ID field to derive unique road networks that were travelled by each person in a week. This feature was referred to as weekly dissolved routes feature class which contained an attribute representing individual weekly travelled distance over unique road networks. A correlation analysis of these three indicators (weekly total distance travelled, weekly total travel time, and weekly unique network distance travelled) shows a positive association, as a result only the unique networks distance travelled measure was used in this research (Figure 4).

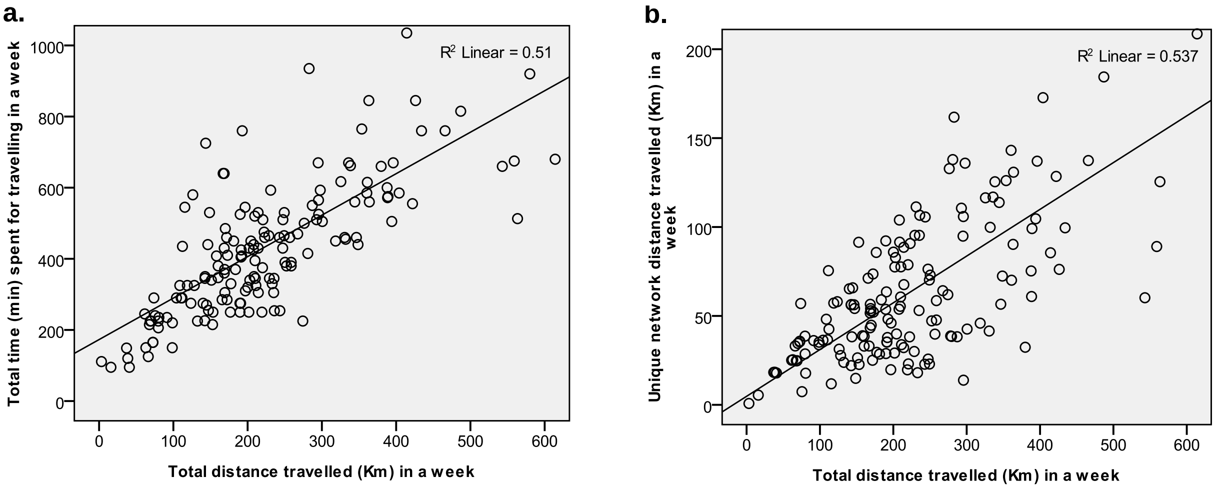


Figure 4: Correlations between the different mobility based measures

In order to identify day to day variation in the levels of individual mobility, the all routes feature class was dissolved using both the person ID and trip day fields to derive scores for daily unique network distance travelled. In a similar way, by adding a 'week' field, the all routes feature class was dissolved based on the person ID field and week field to derive scores for individuals weekdays (from Monday to Friday) and weekends (Saturday and Sunday) mobility. Using these scores, a single-factor ANOVA was conducted in order to investigate the variability in unique network distance travelled between the different days of the week (Table 8). Table 8 shows that this variability is statistically significant between all days of a week. Further investigation shows that distance travelled over unique networks by the individuals is significantly higher on Saturday (about 25 km) and significantly lower on Sunday (about 14 km). As a result, a statistically significant variation was found within weekends (Saturday vs. Sunday). However, no statistically significant variation was found within weekdays (Monday-Friday). This suggests that the weekly (between 7 days) variation that was found to exist is due to a variation between weekdays and weekends (Table 8).

Table 8: Single factor ANOVA test results between the different days in a week using the mobility, activity participation, and accessibility indicators

Indicators	ANOVA groups	DF (within group)	DF (total)	F	Sig (95%)
Unique network distance travelled	Mon vs. Tue vs. Wed vs. Thu vs. Fri vs. Sat vs. Sun	979	985	5.327	Yes
	Mon vs. Tues vs. Wed vs. Thu vs. Fri (weekdays)	728	732	2.217	No
	Sat vs. Sun (weekend)	251	252	15.103	Yes
	Weekdays vs. weekend	308	309	20.295	Yes
Unique locations visited	Mon vs. Tue vs. Wed vs. Thu vs. Fri vs. Sat vs. Sun	979	985	5.707	Yes
	Mon vs. Tues vs. Wed vs. Thu vs. Fri (weekdays)	728	732	2.170	No
	Sat vs. Sun (weekend)	251	252	23.565	Yes
	Weekdays vs. weekend	308	309	95.597	Yes
Accessibility (FDA)	Weekdays vs. weekend	308	309	0.791	No
Accessibility (OATR)	Weekdays vs. weekend	308	309	35.967	Yes

Table 8 also shows that the total degree of freedom (DF) is 985 (986-1) in the seven days measure instead of 1098 given that 157 individuals participated in the survey for seven days (157*7 = 1099). This is due to the fact that 113 diary days were reported empty. This means that respondents did not leave home in these days (one day for 48 individuals, two days for 14 individuals, 3 days for 8 individual, 4 days for 2 individual, 5 days for 1 individual). 4 individuals were found to stay at home both on Saturday and Sunday in the survey. This means that these individuals did not leave home on weekends at all.

3.3.2 Participation based measures

Two measures of participation including the number of unique locations visited in a week and the number of trips were derived in this research. A correlation analysis between these two measures of participation shows that an individuals' number of unique locations visited increased with the number of trips (Pearson Correlation Coefficient 0.489). As a result, only the number of unique locations visited measure is reported in this paper. The destinations feature class was used to derive scores associated with this measure instead of using the OD feature class. This is due to the fact that although a trip is involved with two unique locations such as an origin and a destination, individuals do not participate in activities in the origins. The destinations feature class spatially represents destinations of all trips made by an individual. Since many of these trips were destined to the same geographical locations, the destination feature class was therefore dissolved using the person ID and destination ID as dissolved fields. This operation returned a feature class which represents the unique locations that were visited by each person in the survey week and was referred to as weekly unique destinations. The weekly unique destinations feature class was then summarised using person ID to calculate the number of unique locations visited by each individual.

In order to examine the day to day variations on the level of participation in activities, the destinations feature class was also dissolved using both the person ID and trip day fields to derive scores for daily unique locations visited. In a similar way, the levels of weekdays and weekends participation in activities were also calculated. Using these scores, a similar single-factor ANOVA was conducted. Results from this analysis show that a significant variation on the levels of participation exists between the seven days of a week (Table 8). The average number of unique locations visited is higher on Friday (2.71) and lower on Sunday (2.25). However, no significant variations on the levels of participation in activities were found to exist within weekdays (Monday-Friday) although a significant variation exists within weekends (Saturday vs. Sunday). As a result, a significant variation was observed between weekdays and weekends (Table 8).

3.3.3 Participation type measures

The trip purpose attribute of the destinations feature class was used to measure the types of activity participated in, in a week. A frequency field was added in the destinations feature class which was then populated with a value 1. This feature class was then pivoted based on person ID as input field, trip purpose as pivot field, and frequency as value field. This means that the classified eight activity groups became field headings of the pivoted table and these fields were populated with a value 1 (frequency) if a person participated in that particular type of activity otherwise populated with a value 0 (zero). This pivoted table was then summarised based on person ID as a case field using the Summary Statistics tool. This summary table returned the total number of times an individual participated in different types of activity. Since the participation type measure takes into account whether an individual participated in a particular type of activity or not, the summarised values were therefore recalculated using a Visual Basic Application (VBA) code by adding six new fields in the summary table: shopping_recal, social_recal, recreational_recal, health_recal, food_recal, and other_recal. The code shown below was used to recalculate shopping type of activity and is shown for demonstration purpose only:

```
Dim d as Double
If [Sum_Shopping] > 0 Then
d = 1
Else
d = 0
End If
[Shopping_recal] = d
```

The above code indicates that if a person participated in a shopping activity once or more in the survey week, the shopping_recal field was coded as 1, otherwise 0 (zero). However, work trips were excluded from this analysis in order to maintain the relativity of the measure. This is due to the fact that the non-working individuals do not necessarily participate in the work activities. The return home trip was also excluded from this analysis as this purpose was reported by all individuals. Once the recalculations were done for all six activity types, they were summed up in a new field ‘PT’ (participation type). This means that if an individual participated in all six types of activities, the PT field value was calculated as 6 for that individual.

3.3.4 Accessibility based measures

Three cumulative opportunity based accessibility measures were operationalised in this research using the concept of activity spaces including the standard deviational ellipse (SDE), furthest distance activity (FDA) from home, and opportunities along travelled routes (OATR) measures. However, instead of using the geometric size of activity spaces associated with these measures as a proxy indicator of accessibility, discrete opportunities (non-residential buildings) that were located within these geometric boundaries were used to derive accessibility scores. Previous studies have used the number of opportunities as a measure of accessibility to identify transport disadvantage (Casas, 2007; Casas et al., 2009). However, Ortúzar and Willumsen (1990) have mentioned that measuring accessibility by counting the number of opportunities is misleading. This is due to the fact that some opportunities offer more to satisfy human needs (e.g. a larger sized shopping centre) than others. As a result, this research derived size (area) of the accessible opportunities as a possible way forward in addition to counting the number of opportunities.

The OD feature class was used to derive individuals SDE feature class. The directional distribution tool in ArcGIS was used to derive individuals SDE based on two standard deviations as ellipse size and person ID as case field (Figure 5a). This method takes into account for about 95% of the activity locations to generate the SDEs (ESRI, 2009). In order to calculate the SDE based accessibility, individuals SDEs were selected separately; and the number as well as the area of opportunities that were located within the SDEs was calculated. These calculations were conducted separately for different types (e.g.

recreational) of opportunities for each individual. Since this was a repetitive task, a model was developed and run using the ArcGIS ModelBuilder tool to make this process automatic (Figure 6).

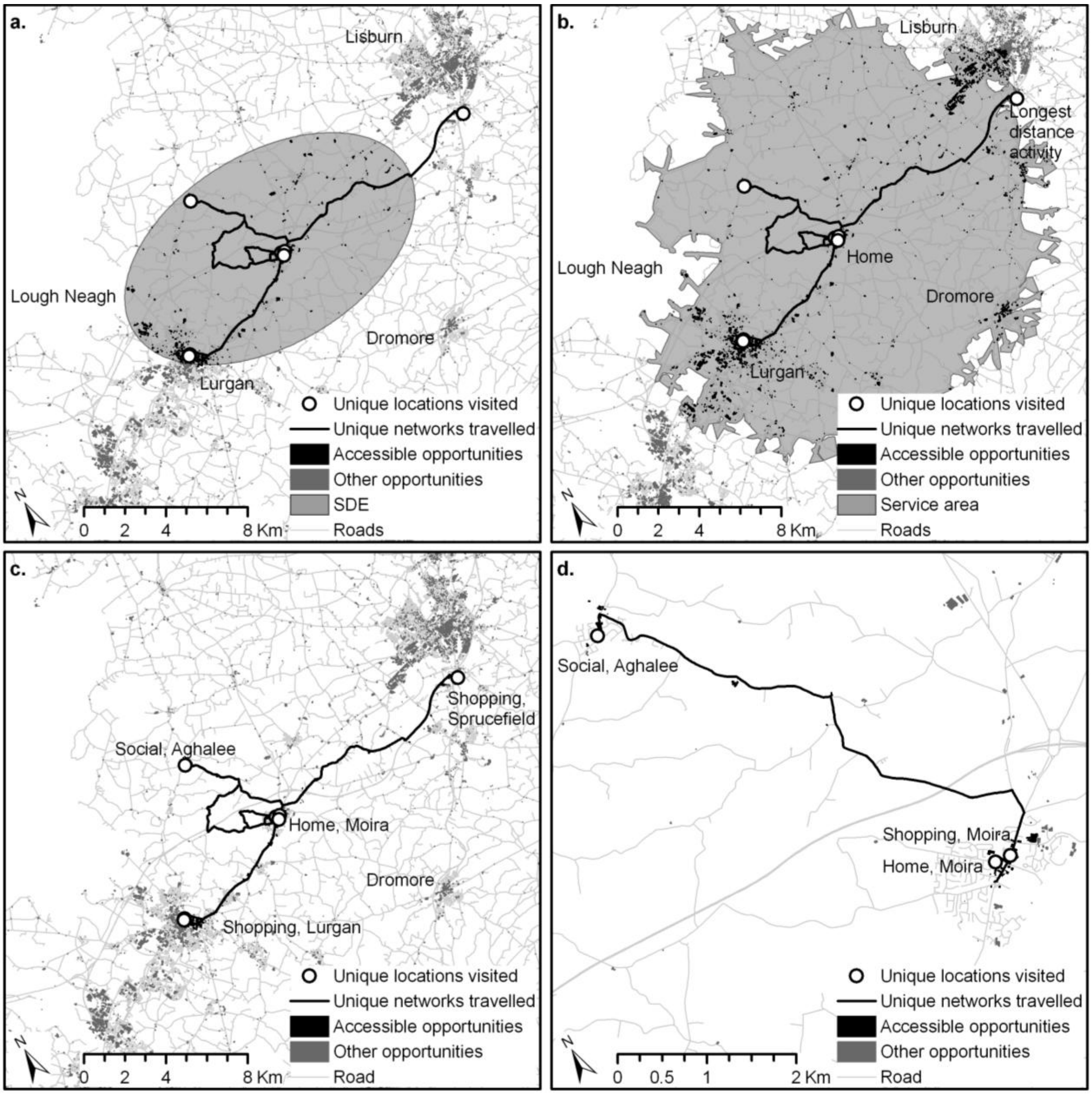


Figure 5: Deriving accessibility using the a) SDE, b) FDA, c) weekdays OATR, d) weekends OATR measures

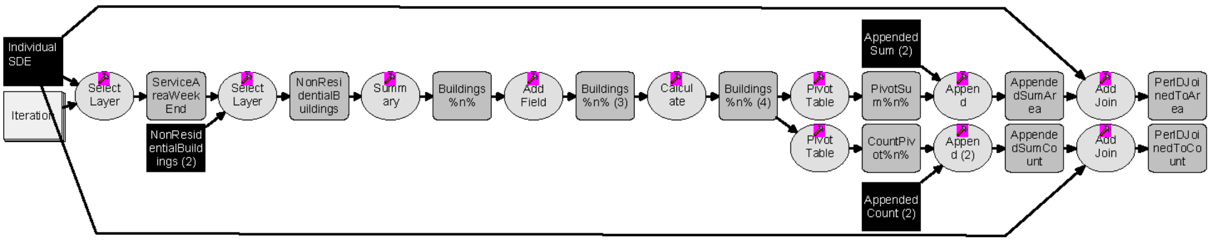


Figure 6: Model used to derive accessibility scores in ArcGIS (version 9.2)

The model used the individuals SDE feature class and the non-residential building feature class as input variables. The individuals SDE feature class contains 157 records, one record is associated with one individual, and is attributed with Object ID and person ID values. Each record of this feature class was selected based on Object ID values (ranges from 1 to 157) using the Select By Attribute tool. This Object ID field was set as an iteration variable in the model. This means that the model ran until all the records of the individuals SDE feature class was selected one by one. The selected SDE in each iteration was then used to select the opportunities that were located within the boundary of the selected SDE from the non-residential building feature class using the Select By Location tool. The selected buildings were then summarised by building type attribute and the number of different types of opportunities (e.g. commercial) as well as their respective sizes (total area) was calculated.

The above operation created a summary table in every iteration; and the name of which was assigned as building%n%. This means that the '%n%' was populated as 0 during the first iteration, 1 during the second iteration, and so on. However, the summary table did not contain any information that could be used to identify the associated person with it. As a result, a new field (temporary person ID) was added during this process. The field value was set to calculate as '%n%+1'. This means that the temporary person ID was populated as 1 during the first iteration, and 2 during the second iteration, and so on. Therefore, these temporary person IDs were identical to the corresponding Object IDs of the individuals SDE feature class based on which the summary tables were created. The generated summary table in each iteration was pivoted using temporary person ID as input field, building type as pivot field, and total area (or total number) as value field. This pivoted table was then appended to an empty table referred to as appended sum (or appended count). At the end of all iterations, the person ID field from the individuals SDE feature class was joined to the appended sum (or appended count) table in order to assign actual person ID associated with these scores.

Using the methodology proposed by Casas (2007) and Casas et al. (2009) the FDA based accessibility score was derived. The shortest path routes from home to all destinations associated with each individual were calculated using distance (metres) as network impedance. For this calculation, the ArcGIS Network Analyst tool was used in which the home feature class was used as origins, and the destinations feature class was used as destinations to generate these routes. Using the distance attribute of these generated routes, the longest distance for each individual was extracted. These longest distances were then used to generate individual service areas (individual service area feature class) from their respective home (Figure 5b). In order to calculate the FDA based accessibility score, the above model was run again but the individual service area feature class was used as input variable instead of the individuals SDE feature class.

Geo-referencing of individual trip routes allowed to derive the meaningful territory of each individual in this research (Golledge, 1999). The number and area of the opportunities that were located along individuals travel routes were derived as a measure of accessibility (OATR measure). The model was run again using the weekly dissolved travel routes feature class as an input variable (instead of the individuals SDE feature class or service area feature class as were used in the earlier approaches) to derive scores for the OATR based accessibility measure. Unlike earlier measures, the model now selected individuals weekly travel routes and opportunities that were located within 200 meters of either side of the routes were selected and processed. Figure 5c and 5d show the accessible opportunities along travel routes of an individual during weekdays and weekends respectively.

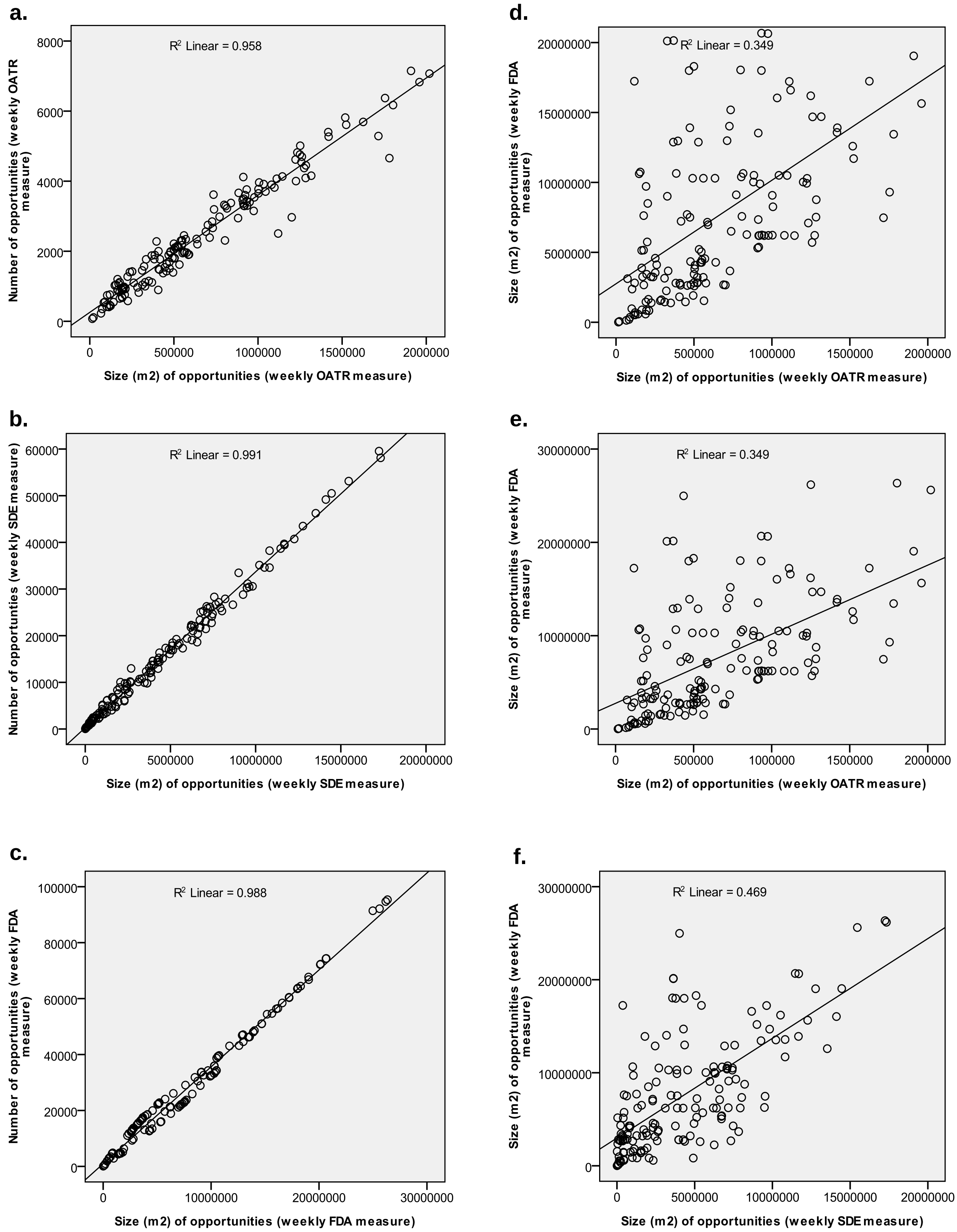


Figure 7: Correlations between different accessibility measures

A correlation analysis between the number and size (area) of opportunities of the three measures shows a significant association (Figure 7a, b, c). As a result, only the size (area) of opportunities is reported in this paper as an indicator of accessibility. However, although a significant association was found to exist between the different measures of accessibility, their explanatory powers (R^2) were found to be relatively weak (less than 50%) As a result, all these three measures were analysed in this research to examine how different groups performed in specific measure.

Using the previous mobility and participation based measures, the most significant temporal variation was found to exist between weekdays and weekends. As a result, using the accessibility scores, the temporal variation was only analysed between weekdays and weekends. Table 8 shows that although a significant variation was evident using the OATR measure, no such variation was found to exist using the FDA based accessibility measure. It was not possible to investigate this difference using the SDE based accessibility measure. This is due to the fact that at least 3 unique activity locations are required in order to operationalise the SDE based measure. Analysis shows that although all individuals visited 3 or more unique activity locations in a week, 16 individuals on weekdays and 34 individuals on weekends visited only 2 unique ODs (including home). As a result, further analyses related to the temporal variation associated with the three measures (mobility, participation, and accessibility) were conducted between weekdays and weekends only.

3.3.5 Accessibility type measure

In order to compare the results obtained from the PTI measure, an accessibility type measure was also developed in this research. Since the participation type measure theoretically ranges from 0 (no participation) to 6 (all types of activity participated in), the accessibility scores associated with different types of opportunities were scaled using the Min-Max scaling method (Equation 1).

$$\text{Scaled score} = \frac{\text{Observed score} - \text{Minimum score}}{\text{Maximum score} - \text{Minimum score}} \qquad \text{Eq.1}$$

The derived scores from the above equation range from 0 to 1. This means that an individual with the maximum number of specific opportunities (e.g. shopping) was scaled to 1 whereas for those individuals who had 0 (zero) accessible opportunities were scaled to 0 for that particular accessibility. These scaled scores were summed up for every individual. As mentioned earlier, six types of opportunities were considered for accessibility analysis. As a result, an individual with the maximum number of accessible opportunities in each of these six categories scored a 6 for the accessibility type measure.

3.3 Data analysis

The explanatory variables used in this research are nominal categories with two categories for the six socio-economic variables (gender, car-ownership, income, occupation, age, and home-ownership) and three categories for the area profile variable (see Table 4). On the other hand, the derived indicators of the different measures (e.g. mobility, participation, and accessibility) were used as dependent variables in order to identify transport disadvantage which are scale (ratio) in nature. Although it was possible to conduct regression analysis using the socio-economic variables as dichotomous variables and coding the area profile variable into two separate dummy variables, the regression analysis does not take into account the interactions amongst the explanatory variables. As identified in Section 1, one of the weaknesses of the previous research studies aiming to identify transport disadvantage is that despite interactions between the explanatory variables, these studies have only considered the main effects of the explanatory factor. Unlike regression analysis, a general linear model (GLM) was found appropriate to this type of analysis because it uncovers both the main as well as the interaction effects for all of the possible combinations of categorical explanatory variables (Bojanic, In Press). Garson (2009) has noted that a main effect is the direct effect of an explanatory variable on the dependent variable whereas an interaction effect is the joint effect of two or more explanatory variables on the dependent variable. In addition, the GLM was tested with and without the interaction effects of the explanatory variable and the results show that the GLM procedure explained a larger variation in the data when the interaction effects were taken into account. The GLM without interaction effects is analogous to the linear multiple regression analysis. However, a separate linear multiple regression analysis was conducted before conducting the GLM in order to check the multicollinearity amongst the explanatory variable. The results of this analysis show that the models met the accepted standard that the part and partial correlations did not drop sharply from zero-order, the tolerance values were not close to zero, and that none of the explanatory variables had a variance inflation factor (VIF) greater than 2 (Xing et al., 2010).

The GLM was constructed to analyse the statistical significance of the seven explanatory variables and their interactions on the different measures of transport disadvantage. All the explanatory variables were entered into the model with full factorial interaction in order to assess the relative importance of various combinations of the explanatory variables. The effect size of the different explanatory variables and their interactions were determined using the Partial Eta Squared which is also called the correlation ratio and is the most common method to measure the effect size (Garson, 2009). The simple contrast method was applied in the GLM which is due to making a comparison of each category (level) of an explanatory variable to the first category (reference) of that explanatory variable. Since the responses were found to be unbalanced meaning that the number of frequencies in different cells were not equal, as a result, the Type III Sum of Square method was used in the models.

4. RESULT

4.1 Differences in the levels of mobility

The GLM tests results shown in Table 9 confirmed that there are significant differences in the levels of mobility between the different groups and at different days in a week. All the three models (weekly, weekdays, and weekends) were found to be significant. The explanatory powers of these models are also acceptable. Analogous to the R-squares of the linear multiple regression models, the Partial Eta Squared of these three models were found to be 0.595, 0.621, and 0.594 respectively. Xing et al. (2010) have mentioned that any models with explanatory power greater than 40% are considered good for a disaggregated analysis. In all three models, car-ownership was found to be a significant contributory factor, the effects of which do not depend on interactions with other explanatory factors. Table 10 shows that the average unique network distance travelled by a car-owning individual is significantly higher than that of a non-car individual in all three periods. The average unique network distance travelled by a car owning individual in weekly, weekdays, and weekends are 70 km, 49 km, and 34 km respectively compared to 34 km, 31 km, and 9 km in respective order for a non-car owning individual. Despite income was found to have a main effect on the levels of weekly mobility, it was found to have an interaction effect with age on weekdays. High income individuals traversed significantly more unique networks (70 km) than their low income counterparts in a week (34 km). However, income was found not to play any influencing role on weekends.

Table 9: GLM tests results showing socio-economic and temporal variations in the levels of mobility

Source	Unique network distance travelled (Km)					
	Weekly		Weekdays		Weekends	
	F	Partial Eta Squared	F	Partial Eta Squared	F	Partial Eta Squared
Corrected model	2.002[a]	0.595	2.233[a]	0.621	1.909[a]	0.594
Intercept	133.765[a]	0.598	121.121[a]	0.574	71.332[a]	0.453
Area profile	2.191	0.046	2.539	0.053	4.220[a]	0.089
Gender	0.000	0.000	0.063	0.001	0.034	0.000
Car-ownership	10.739[a]	0.107	5.977[a]	0.062	6.336[a]	0.069
Income	3.896[a]	0.041	0.955	0.010	3.046	0.034
Age	0.154	0.002	0.235	0.003	0.620	0.007
Occupation	1.703	0.019	0.058	0.001	1.804	0.021
Home-ownership	0.314	0.003	2.172	0.024	0.859	0.010
Interaction						
Area * Age	3.262[a]	0.068	7.123[a]	0.137	7.670[a]	0.151
Income * Age	-	-	4.384[a]	0.046	-	-
Area * Gender * Home	-	-	-	-	4.674[a]	0.052

[a] Coefficients are significant at the 0.05 level

Although the area profile of the respondents and their ages were found to be insignificant as the main effects in the models, interaction of these two explanatory variables was found to be the most significant contributor in the weekdays and weekends models (largest Partial Eta Squared). Although Table 10 shows that the average mobility levels of older individuals are higher than their young counterpart, however, Table 11 shows that this is only true in case of Moira and Doagh. An exactly opposite pattern was found to exist in case of Saintfield where the levels of mobility of older individuals are significantly lower than their young counterparts on weekends. In addition, further investigation found that the level of mobility on weekdays is significantly lower for those young individuals who had low income (33 km) than those who had a higher level of income (49 km). A distinct pattern in the levels of mobility was found to exist on weekends. Although, gender, and home-ownership were found to have an insignificant contributory role as the main effects in the model, these two explanatory factors when coupled with the area profile variable created a significant difference. Table 12 shows that irrespective of the difference in gender or home-ownership status, individuals from Doagh travelled a significantly longer distances than individuals from Moira and Saintfield. As a result, area profile was found to be a significant main contributor in the model for weekends (Table 9). However, individuals from Moira and Saintfield who lived in rented households had a higher level of mobility for being male (43 km and 27 km) than female (11 km and 21 km). As a result, despite living in a rented household, differences were found to exist between Moira and Saintfield for both being male and female (Table 12).

Table 10: Descriptive statistics in the levels of mobility, accessibility, and activity participation

Explanatory variables	Mobility (unique network distance travelled) (Km)			Size (area) of accessible opportunities (Km^2) (FDA measure)			Participation (number of unique activity locations visited)		
Area profile	Weekly	Weekdays	Weekends	Weekly	Weekdays	Weekends	Weekly	Weekdays	Weekends
Moira	60.3736	45.6274	26.2795	8.2084	5.024	4.474	6.87	5.40	3.12
Saintfield	50.9482	35.5311	21.1149	4.6734	3.378	2.463	7.23	4.92	3.48
Doagh	85.8109	60.5619	29.9753	10.9404	7.274	8.706	7.72	5.96	3.63
Gender									
Male	71.2379	49.3422	35.1384	7.7394	5.252	5.678	7.35	5.27	3.60
Female	59.3983	43.9646	25.6208	7.6354	5.080	4.524	7.22	5.49	3.28
Car-ownership									
Non-car owning	33.9151	30.9125	8.7874	4.4346	4.608	1.733	6.29	5.29	2.86
Car-owning	70.3172	49.1906	33.5335	8.2686	5.317	6.002	7.46	5.41	3.52
Income									
Low-income	58.1392	42.8933	26.9109	7.2490	4.818	4.316	6.87	5.20	3.28
High-income	73.1869	50.8645	33.8058	8.2353	5.775	6.444	7.80	5.62	3.60
Age									
Young	58.6556	41.3667	29.6067	6.5621	4.169	4.025	7.02	4.99	3.58
Older	74.0946	54.1035	30.5163	9.3992	6.362	6.447	7.68	6.00	3.19
Occupation									
Working	62.6981	41.5087	32.7693	7.1655	4.102	5.718	6.82	4.73	3.61
Non-working	67.5852	53.1358	26.2923	8.3953	6.230	4.483	7.91	6.30	3.18
Home-ownership									
Owner	67.9032	50.3716	30.4934	7.9561	6.290	4.578	7.48	5.50	3.51
Rented	54.8858	33.9482	28.4071	6.8257	3.438	5.898	6.66	5.03	3.16
Average	64.7525	46.3965	29.9753	7.6825	5.614	5.034	7.28	5.39	3.42

Table 11: Average unique network distance travelled when area profile and age interact

Area profile	Age	Unique network distance travelled (Km)		
		Weekly	Weekdays	Weekends
Moira	Young	48.38	37.48	22.26
	Older	74.09	54.94	30.49
Saintfield	Young	54.53	35.50	25.34
	Older	41.46	35.60	9.93
Doagh	Young	75.28	55.10	44.34
	Older	97.22	66.48	45.12

Table 12: Average unique network distance travelled when area profile, gender, and age interact on weekends

Area profile	Gender	Home-ownership	Unique network distance travelled (Km) in weekends
Moira	Male	Owner	21.99
		Rented	43.01
	Female	Owner	29.54
		Rented	10.90
Saintfield	Male	Owner	23.58
		Rented	27.06
	Female	Owner	17.21
		Rented	20.56
Doagh	Male	Owner	52.58
		Rented	60.25
	Female	Owner	37.06
		Rented	32.16

4.2 Differences in the level of participation in activities

No significant model emerged in the GLM test using the indicator of participation in activities (number of unique locations visited) in a week although car-ownership was found to be a significant contributory factor in this model (Table 13). Similar to the weekly mobility model discussed in previous section, car-owning individuals visited a significantly higher number of unique activity locations (7.46) than their non-car owning counterpart (6.29) (Table 10). Like the weekly participation model, the weekends participation model was also found to be statistically insignificant with no significant contributory factor in this model (Table 13). However, Table 13 shows that the weekdays participation model appeared to be a significant model which accounted around 54% of the variance in data. It also shows that occupation is the only main contributor to this model. Non-working individuals participated in a significantly higher number of unique activity locations on weekdays (6.3) than their working counterpart (4.73). This is due to the fact that working individuals spent most of their time for working on weekdays, and as a result, they had little or no time to participate in other activities. Since most the of working individuals did not participate in work type of activity on weekends, as a result, no difference was found to exist between these two groups in the levels of participation in activities on weekends. Although income and age did not contribute significantly in the weekdays model as a main contributor, a combination of interaction amongst income, age, and occupation was found to be a major contributor in this model. Table 14 shows that amongst the low-income working individuals who were young in age visited least number of unique locations than their older counterpart. On the other hand, amongst the high-income working individuals who were older in age visited fewer opportunities than their young counterpart. However, despite non-working individuals participated in a higher number of unique activity locations, the rate is higher for those non-working individuals who had high-income and older in age.

Table 13: GLM tests results showing socio-economic and temporal variations in the number of unique activity locations visited

Source	Number of unique locations visited					
	Weekly		Weekdays		Weekends	
	F	Partial Eta Squared	F	Partial Eta Squared	F	Partial Eta Squared
Corrected model	1.193	0.467	1.606[a]	0.541	1.118	.462
Intercept	471.399[a]	0.840	389.134[a]	0.812	451.259[a]	.840
Area profile	0.314	0.007	0.584	0.013	0.236	.005
Gender	0.652	0.007	1.485	0.016	0.314	.004
Car-ownership	6.907[a]	0.071	2.722	0.029	1.884	.021
Income	0.240	0.003	0.943	0.010	1.514	.017
Age	3.551	0.038	2.361	0.026	0.029	.000
Occupation	3.311	0.035	5.415[a]	0.057	0.032	.000
Home-ownership	0.693	0.008	0.524	0.006	0.000	.000
Interaction						
Income * Age * Occupation	7.306[a]	0.075	5.450[a]	0.057	-	-

[a] Coefficients are significant at the 0.05 level

Table 14: Average number of unique locations visited when income, age, and occupational characteristics interact

Income	Age	Occupation	Weekly	Weekdays
Low income	Young	Working	5.94	3.90
		Non working	7.50	6.14
	Older	Working	6.91	5.00
		Non working	7.50	6.13
High income	Young	Working	7.47	5.21
		Non working	8.14	6.14
	Older	Working	6.67	5.00
		Non working	9.23	7.00

4.3 Differences in the levels of accessibility

The GLM tests results using the three indicators of weekly accessibility measures (furthest distance activity from home – FDA, opportunities along travel routes – OATR, and standard deviational ellipse – SDE) are shown in Table 15. All models appeared to be statistically significant with good explanatory power. However, the contributions of the different explanatory variables and their interactions were found to be different in each model. Only area profile variable was found to be the common contributory factor in all models. Although age and occupation contributed significantly in the OATR model, these were found to be insignificant contributors in the FDA and SDE models. On the other hand, car-ownership, income, and an interaction between area profile and age variables were found to be significant in the FDA and SDE models although these were found to be insignificant in the OATR model. Despite these differences, investigation shows that the FDA and SDE models are quite closely matched except in explaining two interactions (area profile * gender * income in the FDA model, and area profile * gender * home-ownership in the SDE model) (Table 15). As a result, only the results from the FDA model is reported in this paper because this model accounted a larger part of the variation in data (around 65% when compare to 59% in the SDE model).

Table 15: GLM tests results showing the socio-economic difference in the levels of weekly accessibility by different accessibility measures

Source	Weekly accessibility: size (area) of opportunities (Km^2)					
	FDA measure		OART measure		SDE measure	
	F	Partial Eta Squared	F	Partial Eta Squared	F	Partial Eta Squared
Corrected model	2.513[a]	0.648	2.059[a]	0.602	1.966[a]	0.591
Intercept	128.184[a]	0.588	114.642[a]	0.560	64.882[a]	0.419
Area profile	7.825[a]	0.148	4.205[a]	0.085	3.900[a]	0.080
Gender	0.723	0.008	0.223	0.002	0.000	0.000
Car-ownership	8.102[a]	0.083	0.694	0.008	5.273[a]	0.055
Income	4.574[a]	0.048	1.216	0.013	3.998[a]	0.043
Age	0.233	0.003	4.095[a]	0.044	0.248	0.003
Occupation	0.357	0.004	4.451[a]	0.047	1.438	0.016
Home-ownership	0.017	0.000	3.801	0.041	2.798	0.030
Interaction						
Area * Age	5.783[a]	0.114	-	-	4.539[a]	0.092
Area * Gender * Income	4.579[a]	0.048	-	-	-	-
Area * Gender * Home			4.994[a]	0.053	4.273[a]	0.045

[a] Coefficients are significant at the 0.05 level

Table 10 shows that the level of weekly accessibility is significantly higher for individuals who lived in Doagh (11 km^2) when compare to the level of accessibility of individuals living in Moira (8 km^2). On the other hand, the level of accessibility of individuals living in Saintfield was found to be significantly lower (4.7 km^2) than the level of accessibility of individuals living in Moira (8 km^2). As a result, the level of accessibility of individuals living in Doagh was found to be significantly higher than that of both Moira and Saintfield. This does not necessarily mean that every individual in Doagh had a similar level of accessibility. Since an interaction between area profile and age was found to be a significant contributory factor in the FDA model, further investigation shows that young individuals in Doagh had a lower level of accessibility (9.43 km^2) than older individuals living in Doagh (12.57 km^2) as well as in Moira (9.90 km^2). However, this does not mean that all older individuals had a higher level of accessibility. Older individuals living in Saintfield was found to have a lower level of accessibility (4.29 km^2) than their young counterpart in Saintfield (4.82 km^2). Like the weekly mobility model, the main effect of car-ownership explanatory variable contributed significantly in the FDA accessibility model. Although the main effect of gender is not a significant contributory factor in this model, an interaction of this variable with area profile and income variables contributed significantly in the model. Table 16 shows that although low-income individuals had a lower level of accessibility irrespective of gender in Moira and Doagh, an opposite pattern was found to exist in Saintfield where high-income male had a lower level of accessibility than their low-income male counterpart. It also shows that although individuals from Doagh had a higher level of accessibility, low-income females in this area had a comparatively lower level of accessibility when compared to other groups.

Table 16: Average size (Km^2) of accessible opportunities when area profile, gender, and income interact

Area profile	Gender	Income	Size (area) of accessible opportunities (Km^2) (FDA measure)
Moira	Male	Low income	7.12
		High income	7.77
	Female	Low income	7.81
		High income	10.75
Saintfield	Male	Low income	6.33
		High income	2.62
	Female	Low income	3.31
		High income	6.40
Doagh	Male	Low income	10.54
		High income	13.59
	Female	Low income	8.99
		High income	11.36

Table 17: GLM tests results showing the temporal variation in the levels of accessibility (FDA) by socio-economic characteristics

Source	Weekdays		Weekends	
	F	Partial Eta Squared	F	Partial Eta Squared
Corrected model	2.065[a]	0.596	1.531[a]	0.540
Intercept	74.672[a]	0.451	37.651[a]	0.304
Area profile	4.136[a]	0.083	2.448	0.054
Gender	2.318	0.025	0.036	0.000
Car-ownership	1.028	0.011	4.100[a]	0.046
Income	0.652	0.007	2.009	0.023
Age	0.293	0.003	0.381	0.004
Occupation	0.113	0.001	0.664	0.008
Home-ownership	3.242	0.034	1.264	0.014
Interaction				
Area * Age	7.477[a]	0.141	-	-

[a] Coefficients are significant at the 0.05 level

The temporal variations in the levels of accessibility between weekdays and weekends are shown in Table 17. Both models were found to be significant. The fragmentation of data between weekdays and weekends revealed that car ownership is the main contributor in the levels of individuals accessibility only on weekends but not on weekdays irrespective of areas. This is due to the fact public transport services are not available in these areas on

Sunday and, as a result, a higher level of opportunities are only available to those individuals who had a car irrespective of the area. On the other hand, the interaction between area profile and age remained significant only on weekdays. Further investigation using the different types of opportunities shows similar results in the levels of accessibility between the different groups (Table 18). Similar contribution of different explanatory factors and their interactions were evident in the levels of accessibility using each of the different type of opportunities. Table 18 shows that individuals who had a lower level of accessibility in a certain type of opportunity also had a lower level of accessibility in all types of opportunities.

Table 18: GLM tests results showing the socio-economic differences in the levels of weekly accessibility by type of opportunities

Source	Admin		Commercial		Industrial		Social		Recreation		Other	
	F	Eta^2	F	Eta^2	F	Eta^2	F	Eta^2	F	Eta^2	F	Eta^2
Corrected model	2.43[a]	0.640	2.56[a]	0.652	2.73[a]	0.667	2.303[a]	0.628	2.00[a]	0.596	2.44[a]	0.642
Intercept	131.30[a]	0.593	133.30[a]	0.597	118.83[a]	0.569	124.59[a]	0.581	121.97[a]	0.575	68.98[a]	0.434
Area profile	6.26[a]	0.122	7.84[a]	0.148	11.41[a]	0.202	5.987[a]	0.117	3.36[a]	0.069	6.92[a]	0.133
Gender	0.90	0.010	0.77	0.008	0.49	0.005	0.719	0.008	1.03	0.011	0.10	0.001
Car-ownership	8.70[a]	0.088	8.97[a]	0.091	6.43[a]	0.067	8.540[a]	0.087	7.09[a]	0.073	4.56[a]	0.048
Income	4.49[a]	0.048	4.624[a]	0.049	4.42[a]	0.047	4.716[a]	0.050	4.29[a]	0.046	6.22[a]	0.065
Age	0.43	0.005	0.316	0.003	0.07	0.001	0.133	0.001	0.29	0.003	0.12	0.001
Occupation	0.42	0.005	0.283	0.003	0.39	0.004	0.355	0.004	0.42	0.005	1.53	0.017
Home-ownership	0.01	0.000	0.009	0.000	0.04	0.000	0.023	0.000	0.01	0.000	0.32	0.004
Interaction												
Area*Age	5.82[a]	0.115	5.534[a]	0.110	5.88[a]	0.116	5.977[a]	0.117	5.4[a]	0.107	11.82[a]	0.208
Area*Gender*Income	5.19[a]	0.054	4.891[a]	0.052	3.93[a]	0.042	4.014[a]	0.043	4.05[a]	0.043	-	-
Gender * Home	-	-	-	-	-	-	-	-	-	-	5.21[a]	0.055

[a] Coefficients are significant at the 0.05 level

5. DISCUSSION AND CONCLUSION

One of the objectives of this research was to assess the impacts of mobility and accessibility on individuals levels of participation in activities. In order to reach this objective, different indicators of mobility, accessibility, and participation in activities were derived in this research. Figure 8 is a preliminary result towards meeting this objective which shows that individual levels of accessibility are highly correlated with their levels of mobility (Figure 8a). Although it shows that individual levels of participation in activities also depend on their levels of mobility, this finding is justified for less than 50% individuals in the survey (Figure 8b). In addition, no linear association was found to exist between individual levels of accessibility and their levels of participation in activities (Figure 8c). Figure 8d also confirms that different types of available opportunities do not necessarily ensure participation in all types of activities. Therefore, participation in activities is something that cannot be explained simply by looking at the levels of mobility and accessibility. As a result, this section summarises the findings from the results of the previous section. Table 19 shows the identified disadvantaged groups in each of the three measures operationalised in this research.

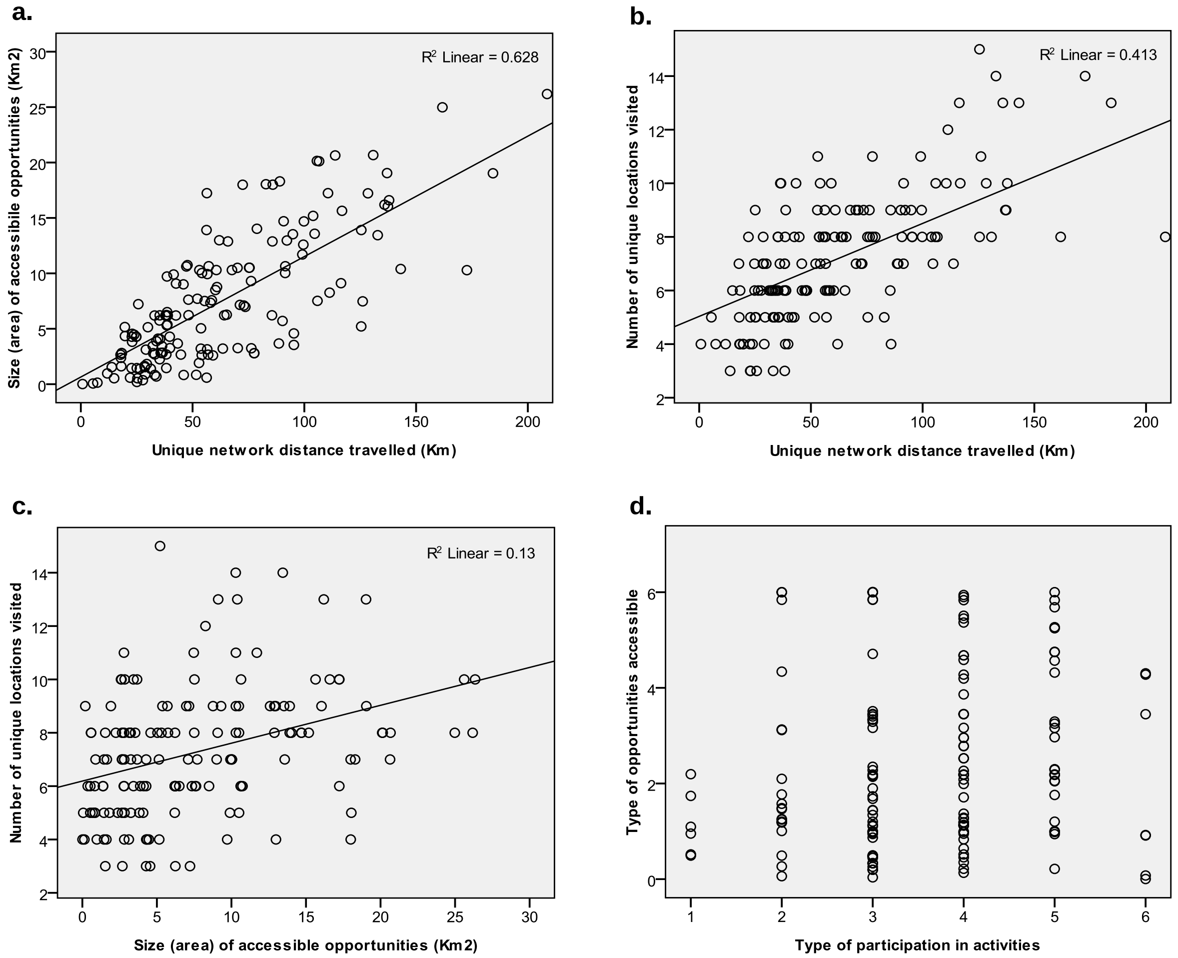


Figure 8: Associations amongst the measures of mobility, accessibility, and participation in activities

Table 19: Identified disadvantaged groups in terms of mobility, accessibility, and participation in activities

Transport disadvantage measures			Identified disadvantaged groups
	Weekdays	Weekends	Overall
Mobility	Non-car owning individuals	Non-car owning individuals	Non-car owning individuals
	Low-income, young individuals	-	Low-income individuals
	Young individuals living in Moira and Doagh	Young individuals living in Moira and Doagh	Young individuals living in Moira and Doagh
	-	Older people living in Saintfield	-
	-	Females living in rented houses in Moira and Saintfield	-
Accessibility	-	Non-car owning individuals	Non-car owning individuals
	Young individuals living in Doagh		Young individuals living in Doagh
	Older individuals living in Saintfield		
			Low-income males and females in Moira and Doagh
			High-income males living in Saintfield
Participation in activities	Low-income, young, working individuals	-	-
	High-income, older, working individuals	-	-

It is clear from Table 19 that despite different groups had a lower level of accessibility and/or mobility, the levels of participation in activities for these groups did not vary significantly. The groups that were identified with a lower level of participation in activities in Table 19 are not due to their lack of accessibility and/or mobility options. Rather they had a lower level of participation in activities due to their lack of time to engage in different activities. This finding therefore suggests concluding that individuals need to participate in activities in any means irrespective of their mobility and/or accessibility restrictions in order to survive in life. As a result, policy interventions should therefore be directed in a way that these activities can be undertaken with relative ease through improving accessibility and mobility options of the identified transport disadvantaged groups.

Groups that have been identified as transport disadvantaged in rural Northern Ireland in earlier research studies include those without their own transport, on low incomes, the young, the less mobile, and the infirm (DARD, 2003; DRD, 2001; 2002). The findings of this research both support and reject the earlier findings. It supports the idea that only the non-car owning group can be identified as transport disadvantaged in all areas and at all times based on both the mobility and accessibility based measures. It also supports the earlier findings that many identified groups (e.g. low-income, the young) are also identified in this research but only in partially. Not all low-income individuals are transport disadvantaged. They are disadvantaged when income level is combined with other factors such as age, gender, and area profile. This is true for other disadvantaged groups as well.

6. REFERENCES

Battellino, H., J. Newman and P. Sayers (2005). City of Sydney: analysis of transport disadvantage. MSW Ministry of Transport and The City of Sydney Council, Consultant report.

Becker, U. and R. Gerike (2008). Background - Needs as the Focus of Transport Planning. In: How to Define and Measure Access and Need Satisfaction in Transport (U. Becker, J. Böhmer, R. Gerike, eds.), pp. 5-24. Dresdner Institut für Verkehr und Umwelt e.V. (DIVU), Dresden.

Bojanic, D. C. (In Press). The impact of age and family life experiences on Mexican visitor shopping expenditures. Tourism Management, doi:10.1016/j.tourman.2010.03.012.

Buliung, R. N. and P. S. Kanaroglou (2006a). A GIS toolkit for exploring geographies of household activity/travel behaviour. Journal of Transport Geography, 14, 35-51.

Buliung, R. N. and P. S. Kanaroglou (2006b). Urban Form and Household Activity-Travel Behavior. Growth and Change, 37, 172-199.

Buliung, R. N. and T. K. Remmel (2008). Open source, spatial analysis, and activity-travel behaviour research: capabilities of the aspace package. Journal of Geographical Systems, 10, 191-216.

Buliung, R. N., M. J. Roorda and T. K. Remmel (2008). Exploring spatial variety in patterns of activity-travel behaviour: initial results from the Toronto Travel-Activity Panel Survey (TTAPS). Transportation, 35, 697-722.

Burchardt, T., J. L. Grand and D. Piachaud (1999). Social Exclusion in Britain 1991-1995. Social Policy & Administration, 33, 227-244.

Burchardt, T., J. L. Grand and D. Piachaud (2002). Degrees of Exclusion: Developing a Dynamic, Multi-Dimensional Measure. In: Understanding Social Exclusion (J. Hills, J. L. Grand, D. Piachaud, eds.), pp. 30-43. Oxford University Press, Oxford.

Casas, I. (2007). Social Exclusion and the Disabled: An Accessibility Approach. The Professional Geographer, 59, 463-477.

Casas, I., M. W. Horner and J. Weber (2009). A Comparison of Three Methods for Identifying Transport-Based Exclusion: A Case Study of Children's Access to Urban Opportunities in Erie and Niagara Counties, New York. International Journal of Sustainable Transportation, 3, 227 – 245.

Cass, N., E. Shove and J. Urry (2005). Social exclusion, mobility and access. The Sociological Review, 53, 539-555.
Cebollada, À. (2009). Mobility and labour market exclusion in the Barcelona Metropolitan Region. Journal of Transport Geography, 17, 226-233.
Church, A., M. Frost and K. Sullivan (2000). Transport and social exclusion in London. Transport Policy, 7, 195-205.
Cloke, P., P. Milbourne and C. Thomas (1994). Lifestyles in Rural England. A Research Report to the Department of the Environment and the Economic and Social Research Council and the Rural Development Commission.
Currie, G., T. Richardson, P. Smyth, D. Vella-Brodrick, J. Hine, K. Lucas, J. Stanley, J. Morris, R. Kinnear and J. Stanley (2009). Investigating links between transport disadvantage, social exclusion and well-being in Melbourne--Preliminary results. Transport Policy, 16, 97-105.
Currie, G. and J. Stanley (2008). Investigating Links between Social Capital and Public Transport. Transport Reviews, 28, 529-547.
DARD (2003). A Guide to Rural Proofing: Considering the Needs of Rural Areas and Communities. Department of Agriculture and Rural Development, Belfast.
DfT (2006). Social Inclusion: Transport Aspects (Final Report). Department for Transport, London.
DRD (2001). Shaping Our Future: Regional Development Strategy for Northern Ireland 2025. Department for Regional Development, Belfast.
DRD (2002). Regional Transportation Strategy for Northern Ireland 2002 - 2012. Department for Regional Development, Belfast.
ESRI (2009). Directional Distribution (Standard Deviational Ellipse) (Spatial Statistics). Environmental Systems Research Institute (ESRI), www.esri.com Accessed on October 7, 2009.
Farrington, J. and C. Farrington (2005). Rural accessibility, social inclusion and social justice: towards conceptualisation. Journal of Transport Geography, 13, 1-12.
Farrington, J. H. (2007). The new narrative of accessibility: its potential contribution to discourses in (transport) geography. Journal of Transport Geography, 15, 319-330.
Garson, D. (2009). Univariate GLM, ANOVA, and ANCOVA. North Carolina State University, http://faculty.chass.ncsu.edu/garson/PA765/anova.htm June 10, 2010.
Goldhaber, R. and I. Schnell (2007). A model of multidimensional segregation in the Arab Ghetto in Tel Aviv-Jaffa. Tijdschrift voor Economische en Sociale Geografie, 98, 603-620.
Golledge, R. G. (1999). Human wayfinding and cognitive Maps. In: Wayfinding Behavior (R. G. Golledge, ed.), pp. The Johns Hopkins University Press, Baltimore.
Golledge, R. G. and R. J. Stimson (1997). Spatial behaviour: A geographic perspective. The Guilford Press, New York.
Gray, D. (2000). How much of a problem is rural transport in Scotland? Policy Paper Series 1, The Centre for Transport Policy.
Higgs, G. and S. White (2000). Alternatives to census-based indicators of social disadvantage in rural communities. Progress in Planning, 53, 1-81.
Hine, J. and M. Grieco (2003). Scatters and clusters in time and space: implications for delivering integrated and inclusive transport. Transport Policy, 10, 299-306.
Hine, J. and F. Mitchell (2001). The Role of Transport in Social Exclusion in Urban Scotland. Scottish Executive Central Research Unit, Edinburgh.
Hine, J. and F. Mitchell (2003). Transport Disadvantage and Social Exclusion: Exclusionary mechanisms in transport in urban Scotland. Ashgate, Hampshire.
Hodge, I., J. Dunn, S. Monk and M. Fitsgerald (2002). Barriers to participation in residual rural labour markets. Work, Employment & Society, 16, 457-476.
Hurni, A. (2006). Transport and social disadvantage in Western Sydney: a partnership research project. Western Sydney Community Forum, New South Wales.
Jain, J. and J. Guiver (2001). Turning the Car Inside Out: Transport, Equity and Employment. Social Policy & Administration, 35, 569-586.
Kamruzzaman, M., J. Hine, B. Gunay and N. Blair (In Press). Using GIS to visualise and evaluate student travel behaviour. Journal of Transport Geography, doi: 10.1016/j.jtrangeo.2009.09.004.
Kawase, M. (1999). Commuting activity spaces of married women in a suburb of the Tokyo metropolitan area. GeoJournal, 48, 217-222.

Kenyon, S., G. Lyons and J. Rafferty (2002). Transport and social exclusion: investigating the possibility of promoting inclusion through virtual mobility. Journal of Transport Geography, 10, 207-219.
Kim, H.-M. and M.-P. Kwan (2003). Space-time accessibility measures: A geocomputational algorithm with a focus on the feasible opportunity set and possible activity duration. Journal of Geographical Systems, 5, 71-91.
Knowles, R. D. (2006). Transport shaping space: differential collapse in time and space. Journal of Transport Geography 14, 407-425.
Kwan, M.-P. (1998). Space–time and integral measures of individual accessibility: a comparative analysis using a point-based framework. Geographical Analysis, 30, 191–216.
Kwan, M.-P. (1999). Gender and Individual Access to Urban Opportunities: A Study Using Space-Time Measures. The Professional Geographer, 51, 211-227.
Kwan, M.-P. and X.-D. Hong (1998). Network-based constraints-oriented choice set formation using GIS. Geographical Systems, 5, 139-162.
Kwan, M.-P. and J. Weber (2008). Scale and accessibility: Implications for the analysis of land use-travel interaction. Applied Geography, 28, 110-123.
Lucas, K. (2006). Providing transport for social inclusion within a framework for environmental justice in the UK. Transportation Research Part A, 40, 801-809.
McCray, T. and N. Brais (2007). Exploring the Role of Transportation in Fostering Social Exclusion: The Use of GIS to support Qualitative Data. Networks and Spatial Economics, 7, 397-412.
McDonagh, J. (2006). Transport policy instruments and transport-related social exclusion in rural Republic of Ireland. Journal of Transport Geography, 14, 355-366.
Miller, H. J. (1991). Modelling accessibility using space–time prism concepts within geographical information systems. International Journal of Geographical Information Systems, 5, 287-302.
Miller, H. J. (1999). Measuring space-time accessibility benefits within transportation networks: Basic theory and computational procedures. Geografical Analysis, 31, 287-301.
Mohr, C. O. (1947). Table of Equivalent Populations of North American Small Mammals. American Midland Naturalist, 37, 223-249.
Moseley, M. A. (1979). Accessibility: The rural challenge. Methuen, London.
Newsome, T. H., W. A. Walcott and P. D. Smith (1998). Urban activity spaces: Illustrations and application of a conceptual model for integrating the time and space dimensions. Transportation, 25, 357-377.
Nutley, S. (1985). Planning options for the improvement of rural accessibility: use of the time-space approach. Regional Studies, 19, 37-50.
Ortúzar, J. d. D. and L. G. Willumsen (1990). Modelling Transport. John Wiley & Sons, Chichester.
Páez, A. (2006). Exploring contextual variations in land use and transport analysis using a probit model with geographical weights. Journal of Transport Geography, 14, 167-176.
Parkes, D. and N. Thrift (1980). Times, spaces and places. John Wiley & Sons, Chichester.
Preston, J. and F. Rajé (2007). Accessibility, mobility and transport-related social exclusion. Journal of Transport Geography, 15, 151-160.
Rajé, F., M. Grieco, J. Hine and J. Preston (2003). Impacts of road user charging/workplace parking levy on social inclusion/exclusion, gender, ethnicity and lifecycle issues. Final Report, DfT, London.
Rogalsky, J. (In Press). The working poor and what GIS reveals about the possibilities of public transit. Journal of Transport Geography, doi:10.1016/j.jtrangeo.2009.06.008.
Rollinson, P. A. (1991). The Spatial Isolation of Elderly Single-Room-Occupancy Hotel Tenants. The Professional Geographer, 43, 456-464.
Schönfelder, S. (2001). Some notes on space, location and travel behaviour. 1st Swiss Transport Research Conference, Monte Verita/Ascona, 1-18.
Schönfelder, S. and K. W. Axhausen (2003). Activity spaces: measures of social exclusion? Transport Policy, 10, 273-286.
Seamon, D. (1979). A Geography of the Lifeworld. Croom Helm, London.
SEU (2003). Making the Connections: Transport and Social Exclusion. Social Exclusion Unit, The Stationery Office, London.
Shortall, S. (2008). Are rural development programmes socially inclusive? Social inclusion, civic engagement, participation, and social capital: Exploring the differences. Journal of Rural Studies, 24, 450-457.

Stanley, J. and K. Lucas (2008). Social exclusion: What can public transport offer? Research in Transportation Economics, 22, 36-40.

Stanley, J. and J. Stanley (2004). Improving Public Transport to Meet Community Needs: A Warrnambool Case-study. Bus Association Victoria and Warrnambool Bus Lines, Melbourne.

Stanley, J. and D. Vella-Brodrick (2009). The usefulness of social exclusion to inform social policy in transport. Transport Policy, 16, 90-96.

Verron, H. (2008). Do We Need a New Approach on Access for Assessing Benefits of Transport Infrastructure Investment? Theses in the Environmental Point of View. In: How to Define and Measure Access and Need Satisfaction in Transport (U. Becker, J. Böhmer, R. Gerike, eds.), pp. 25-33. Dresdner Institut für Verkehr und Umwelt e.V. (DIVU), Dresden.

Weber, J. and M.-P. Kwan (2002). Bringing Time Back In: A Study on the Influence of Travel Time Variations and Facility Opening Hours on Individual Accessibility. The Professional Geographer, 54, 226-240.

Weber, J. and M.-P. Kwan (2003). Evaluating the effects of geographic contexts on individual accessibility: A multilevel approach. Urban Geography, 24, 647-671.

White, S. E. (1985). Macro-level activity spaces: some nationwide visitation patterns. The Professional Geographer, 37, 28-35.

Wilson, L. (2006). Developing a model for the measurement of social inclusion and social capital in regional Australia. Social Indicators Research, 74, 335-360.

Wu, B. M. and J. Hine (2003). A PTAL approach to measuring the changes in bus service accessibility. Transport Policy, 10, 307-320.

Wyllie, D. S. and G. C. Smith (1996). Effects of Extroversion of the Routine Spatial Behavior of Middle Adolescents. The Professional Geographer, 48, 166-180.

Xing, Y., S. L. Handy and P. L. Mokhtarian (2010). Factors associated with proportions and miles of bicycling for transportation and recreation in six small US cities. Transportation Research Part D, 15, 73-81.

Yu, H. and S.-L. Shaw (2008). Exploring potential human activities in physical and virtual spaces: a spatio-temporal GIS approach. International Journal of Geographical Information Science, 22, 409–430.