Car ownership as a mediating variable in car travel behavior research using a structural equation modelling approach to identify its dual relationship

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Car ownership as a mediating variable in car travel behaviour research. A structural equation modelling approach

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Abstract

Car ownership is generally considered an important variable in car travel behaviour research, but its specific role is often not well understood. Certain empirical studies consider car ownership as the dependent variable explained by the built environment, whereas other studies deem it to be one of the independent variables explaining car travel behaviour. This paper takes note of the dual influence car ownership has in explaining car travel behaviour by assuming that car ownership mediates the relationship between the built environment and car use. The relationship is estimated using a structural equation model since it accounts for mediating variables. This approach confirms the intermediary nature of car ownership.

Keywords: car use, car ownership, structural equation model, Ghent.

1. Introduction

Like in most countries, the overall amount of travel in Belgium has increased substantially. Within 10 years time, total travel distance by car has increased by a quarter: from 60 billion vehicle-kms in 1990 to 75 billion vehicle-kms in 2000 (http://www.mobilit.fgov.be/). Because travel is associated with negative externalities such as congestion and pollution, policymakers try to control and manage travel patterns. Illustrative are the New Urbanism movement in the United States and the Compact City Policy in Europe, that aim at reducing car use and travel distances through urban planning. The basic idea is that high-density and mixed-use neighbourhoods are believed to be associated with shorter trips and more non-motorized trips; hence, indicating a clear existing relationship between the built environment and travel behaviour.

So far, many studies exist that try to determine the relationship between the built environment and travel behaviour. Within this research debate, car ownership is considered as mediating the relationship between the built environment and travel behaviour. A theoretical justification for this is given by Ben-Akiva and Atherton (1977). They embedded the built environment, car ownership and travel behaviour in a hierarchy of choices. Car ownership is considered to be a medium-term decision, which is influenced by long-term decisions such as place of employment and residential locational choice. The spatial characteristics of these locations, such as the availability of public transport, constrain or facilitate car ownership. Car ownership, in turn, affects short-term decisions such as daily car use of individuals and households.

However, most empirical studies do not consider car ownership as a mediating variable. Car ownership is mainly used as an exogenous variable, in addition to spatial and socio-economic variables, to explain travel behaviour (e.g., Bagley and Mokhtarian, 2002; Dieleman et al., 2002; Krizek, 2003; Schwanen et al., 2002). On the other hand, some studies consider car ownership as an endogenous variable and try to explain it based on various spatial and socio-economic variables (e.g., Bhat and Guo, 2007; Cao et al., 2007a; Dargay, 2002; Giuliano and Dargay, 2006). Only a limited amount of studies combines both research approaches and considers car ownership as mediating the relationship between the built environment and travel behaviour (e.g., Cao et al., 2007b; Scheiner and Holz-Rau, 2007; Schimek, 1996; Simma and Axhausen, 2003). Travel behaviour is, then, directly determined by car ownership and the built environment, and car ownership itself is also influenced by the built environment. This results in an indirect effect of the built environment on travel behaviour through the mediating variable car ownership. Although car ownership is considered as a mediating variable, none of these studies really discussed the consequences of ignoring this. Therefore, this paper will highlight the consequences by comparing the results of a structural equation model with car ownership as a mediating variable with the results of a structural equation model without this.

The aim of this paper is to contribute to our understanding of the role of car ownership as a mediating variable, and specifically in relation to daily car use. The paper is structured as follows. Section 2 presents a brief literature review on the relationship between the built environment and (car) travel behaviour. In particular, attention is paid to the role and importance car ownership plays in explaining this relationship. Section 3 describes a suitable methodological technique that is able to deal with the ambiguous role of car ownership. Here structural equation modelling is advanced. A structural equation model (SEM) can simultaneously handle relationships between several exogenous and endogenous variables and, as a consequence, it is able to model mediating variables. The analysis (Section 5) is preceded by a discussion of the used dataset, which is explained in Section 4. Finally, in Section 6, our most important findings are summarized and discussed.

2. Literature review

There are many studies that focus on the relationship between the built environment and (car) travel behaviour. As a consequence, an enormous variety of variables have been taken into consideration. This section briefly summarizes some of the relevant literature on car ownership and (car) travel behaviour (for more comprehensive reviews, see, e.g., Handy, 2005; Stead and Marshall, 2001; Van Acker and Witlox, 2005).

2.1 The built environment and travel behaviour

The effects of *spatial density* on travel demand have long been acknowledged (e.g., Levinson and Wynn, 1963) and remain well-studied and understood. Higher spatial densities are associated with lower car ownership and more public transport use, less car use, and more walking and cycling. After all, in high-density areas public transport is organized more efficiently (more routes, higher frequency of services) and higher densities are also associated with higher levels of congestion (Schwanen et al., 2004). Also, in dense areas people tend to travel shorter distances and they spend less time travelling on average (Cervero and Kockelman, 1997; Dargay and Hanly, 2004; Hammadou et al., 2008; Kitamura et al., 1997; Schwanen et al., 2004; Stead, 2001).

A second issue is *spatial diversity*. Several indicators have been developed to measure diversity: among others, a jobs/housing ratio (Boarnet and Sarmiento, 1998; Ewing et al., 1994), an entropy index to quantify the degree of balance across various land use types (Frank and Pivo, 1994; Kockelman, 1997) or a (dis)similarity index to indicate the degree to which different land uses lie within a person's surrounding (Kockelman, 1997). The effects of more diversity on car ownership and (car) travel behaviour are comparable to the effects of higher densities.

A third dimension is *spatial design.* It can be characterized by a general classification of neighbourhoods with a standard suburban neighbourhood and a neo-traditional neighbourhood as extremes (Gorham, 2002; McNally and Kulkarni, 1997). Standard suburban neighbourhoods are characterized by low densities, limited diversity, and a car-orientated design. These neighbourhoods are associated with more cars per capita and more car use. Spatial design however also relates to site design, and dwelling and street characteristics. Neighbourhoods characterized by small block sizes, a complete sidewalk system, the absence of cul-de-sacs and limited residential parking tend to encourage walking and cycling (Cervero and Kockleman, 1997; Hess et al., 1999; Stead, 2001). Meurs and Haaijer (2001) noted that, although characteristics of the dwelling, street, and neighbourhood may influence modal choice, this is only true for shopping and social or recreational purposes. Working trips are less likely to be influenced by spatial design characteristics.

Accessibility is a fourth important characteristic of the built environment which generally refers to the ability "to reach activities or locations by means of a (combination of) travel mode(s)" (Geurs and van Wee, 2004). Most studies pointed out that accessibility is negatively associated with car ownership (e.g., Chen et al., 2008; Gao et al., 2008; Kockelman, 1997; Simma and

Axhausen, 2003). Rajamani et al. (2003) found that higher accessibility by a given mode is likely to result in higher usage of that mode. For example, households living in neighbourhoods that are easily accessible by public transport tend to make more trips by public transport (Kitamura et al., 1997). Similarly, individuals that have several facilities and services such as a shops, banks, schools and doctors within walking distance of their residence undertake more walk trips and less car trips (Simma and Axhausen, 2003). However, some confounding results exist related to the influence of accessibility by car on car use. Some studies (e.g., Rajamani et al., 2003) found that better accessibility by car results in more car use, whereas other studies state the opposite (e.g., Kockelman, 1997). Despite high levels of car accessibility, Kockelman (1997) argued that less car use might still occur since higher accessibility is generally associated with higher land prices, less convenient parking options and more roadway congestion.

2.2 Socio-economic and demographic differences in travel behaviour

Empirical studies focusing on the relationship between the built environment and travel behaviour should also control their results for various socio-economic and demographic characteristics of the individual and the household. *Age* is an important variable. Car ownership and car use tend to be lower among older persons (aged above 65 years). Moreover, if older persons travel by car, they are likely to travel shorter distances. Note also that older persons not only travel because they want to participate in activities, the travelling itself can have certain socializing opportunities. Ride-sharing for non-work trips is, therefore, found to increase by age (Boarnet and Sarmiento, 1998; Dargay and Hanly, 2004; Schwanen et al., 2004; Stead, 2001).

Gender is another important variable. The difference in travel behaviour between women and men depend on trip purpose. Other findings can be formulated whether work travel or non-work travel is analyzed. Women are inclined to commute more often by public transport, by bike or on foot, whereas car use tends to be higher among men for work trips. Moreover, commuting distances and times appear to be shorter for women (Schwanen et al., 2002, 2004; Stead, 2001). This gender difference is partly explained by the fact that women earn lower wages, and fulfil other types of jobs (Hanson and Pratt, 1988; Madden, 1981). Because women remain primarily responsible for most household maintenance tasks, some studies (e.g., Boarnet and Sarmiento, 1998) specify that women use a car more often and travel longer distances for non-work trips. However, other studies (e.g., Schwanen et al., 2002) found the opposite: women spend less time on car travel for shopping purposes than men do. This indicates that women are more likely to travel to shops within walking or cycling distance from their residence.

Educational level, *employment* status, and *income* are related variables, thus resulting in comparable findings. Hence, highly educated persons often obtain more specialized jobs which are generally concentrated in high-density or central business district office parks. As a result, higher educated are more involved in long-distance commuting and their car use is higher (Boarnet and Sarmiento, 1998; Dargay and Hanly, 2004; Dieleman et al., 2002; Kockelman, 1997; Krizek, 2003; McNally and Kulkarni, 1997; Schwanen et al., 2002, 2004; Stead, 2001). However, the use of public transport, especially train use, might also be higher if these high-density or central business centre office parks are located nearby a railway station.

Household size is positively associated with car ownership. Because of intra-household decisions related to the activities of several household members, the need to own more than one car increases within larger households. Households that own several cars are likely to use their cars more often. Furthermore, because of their possibly stronger car dependency, members of larger households tend to travel longer distances (Dargay and Hanly, 2004; Kockelman, 1997). Comparable results can be found with respect to the number of employed persons in the household (Cervero and Kockelman, 1997; Krizek, 2003) and, to some degree, to the presence of children. Since they do not have to spend time on child care responsibilities, singles and childless couples tend to obtain longer total daily travel times (Boarnet and Sarmiento, 1998; Dargay and Hanly, 2004; Dieleman et al., 2002; Schwanen et al., 2002; Stead, 2001).

Several studies use *car ownership* as an independent variable in order to explain travel behaviour. Car use seems on average higher among households owning several cars than among household without a car (Dieleman et al., 2002). Moreover, owning a car enables people to travel longer distances compared to people that must rely on slower modes such as public transport, walking and biking (Bagley and Mokhtarian, 2002; Krizek, 2003; Schwanen et al., 2002). On the other hand, car ownership in itself is influenced by other socio-economic variables, especially income. Car ownership is generally higher among high-income groups (Dargay and Hanly, 2004; Kockelman, 1997; Soltani, 2005; Whelan, 2007).

2.3 The built environment or the individual and its household ?

There seems to be a lot of literature confirming the relationship between the built environment and travel behaviour. Kockelman (1997) stressed that, after demographic characteristics were controlled for, the built environment still proved to have an important influence on travel behaviour. Similar conclusions have been made by, e.g., Dargay and Hanly (2004) and Zhang (2004). Meurs and Haaijer (2001) refined these findings. According to their analyses the built environment has a significant influence on non-work travel, whereas work travel is almost entirely determined by personal characteristics. Dieleman et al. (2002) found an equal influence of the built environment and personal characteristics. On the other hand, several studies point out that the built environment has only a moderate effect on travel behaviour (e.g., Cervero and Kockelman, 1997; Schwanen et al., 2004; Simma and Axhausen, 2003; Stead, 2001).

Moreover, there is a fundamental question of causation in any of the previously mentioned studies (Handy et al., 2005; Kockelman, 1997). Based on these studies, it seems that in certain circumstances the built environment may have a statistically significant influence on travel behaviour. However, statistical results can mask underlying linkages that are more important and of which the built environment characteristics are only a proxy. For example, most recently, there is a growing body of literature on the relationship between the built environment and personal characteristics (e.g., Bagley and Mokhtarian, 2002; Bhat and Guo, 2007; Cao et al., 2006, Pinjari et al., 2007). This research question refers to the issue of residential self-selection: people might self-select themselves into different residential neighbourhoods. Or in other words, people may choose their residential neighbourhood according to their personal attitudes and preferences. For example, people's residential location decision might be based on their travel preferences, so that they are able to travel according to these preferences. Consequently, the connection between the built environment and travel behaviour is more a matter of personal attitudes and preferences. Moreover, this suggests that the influence of the built environment can not be exogenously determined from these personal characteristics. This is confirmed by Bagley and Mokhtarian (2002) and Cao et al. (2006): i.e. after controlling for residential self-selection, the built environment was found to have little effect on travel behaviour. However, Bhat and Guo (2007) and Pinjari et al. (2007) state the opposite.

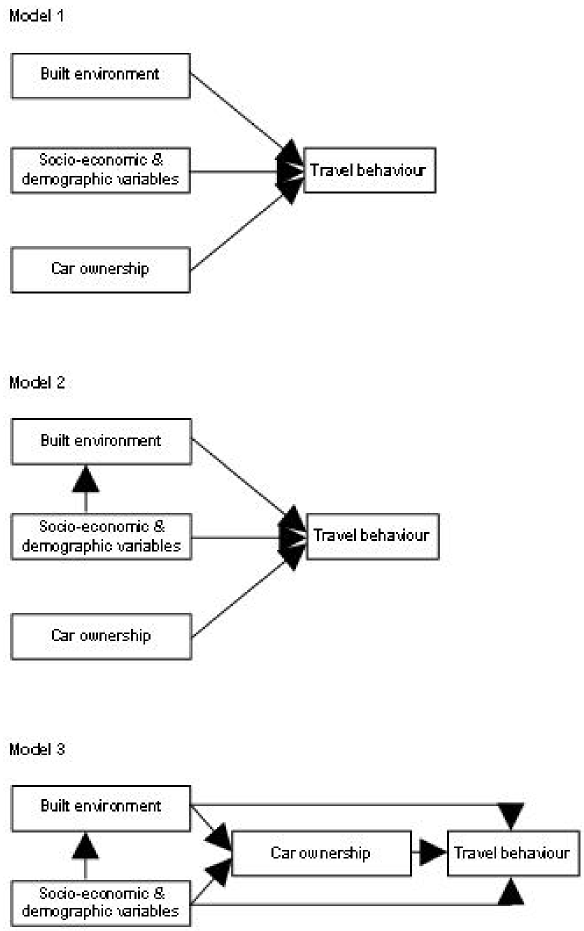
2.4 Conceptual model

Based on the previous literature review, several possible effects can be postulated between the built environment and travel behaviour. Figure 1 represents these model structures with increasing degree of complexity. The models can be applied to all aspects of travel behaviour, but our analysis is limited to mode choice and car use in particular.

The first model shown in Figure 1 resembles a frequently used approach in research on the relationship between the built environment and travel behaviour. In this model, travel behaviour is directly influenced by the built environment, various socio-economic and demographic variables, and car ownership. Model 1 considers car ownership as a variable explaining travel behaviour, but it does not consider car ownership as a mediating variable. Consequently, this model does not result in indirect effects of the built environment and socio-economic and demographic variables on travel behaviour. Since it does not include any relationships between the explanatory variables, this first model can be analyzed by means of a regression analysis. By assuming a relationship from personal characteristics to the built environment, the second model partly accounts for the issue of residential self-selection[1]. As a result, indirect effects of personal characteristics on travel behaviour will occur. Finally, in the third model we seek to reveal the importance of car ownership as a mediating variable while partly controlling for residential self-selection. In doing so, indirect effects of the built environment on travel behaviour occur as well. Mediating variables occur in models 2 and 3, and thus structural equation models must be estimated. Since all models are hierarchically nested in each other, we can compare the models' goodness-of-fit indices. Doing so, we are able to determine the improvement of each model compared to the previous one. Consequently, we can verify the intermediary effect of car ownership on travel behaviour, while partly controlling for residential self-selection.

[1] Model 2 in Figure 1 partly accounts for residential self-selection since it only does so with respect to observed personal variables. Mokhtarian and Cao (2008) mention two sources from which residential self-selection occur: personal characteristics and attitudes. Since our data source does not include information on attitudes, we can only consider a relationship between personal characteristics and the built environment.

Figure 1. Conceptual models describing the relationships between the built environment and travel behaviour



3. Methodology of structural equation modelling

The brief literature review highlights the complex relationship between the built environment and travel behaviour. Several variables must be accounted for and, moreover, these variables can influence each other as well. For example, car ownership can act as a mediating variable between the built environment and travel behaviour. Consequently, car ownership is the outcome variable (or dependent variable) in one set of relationships and at the same time it is a predictor (or explanatory variable) of travel behaviour. Structural equation modelling seems a suitable methodological technique since it can deal with such complex relationships.

Structural equation modelling is a research technique dating from the 1970s. Most applications have been in economics, psychology, sociology, the biological sciences, educational research, political science and marketing research. It is only recently that a structural equation model (SEM) has been applied to understand the relationship between the built environment and (car) travel behaviour (e.g., Bagley and Mokhtarian, 2002; Cao et al., 2007b; Chung et al., 2004; Van Acker et al., 2007).

Structural equation modelling can be considered as a combination of factor analysis and regression analysis. The factor analysis aspect in a SEM refers to the modelling of indirectly observed (or latent) variables of which the values are based on underlying manifest variables (or indicators) which are believed to represent the latent variable. The measurement model, therefore, defines the relationships between a latent variable and its indicators. However, since all variables in our data source are directly observed (manifest variables), this paper is solely based on the regression analysis aspect of SEM. Therefore, our results are based on the estimation of a series of simultaneously estimated structural (i.e. regression) equations. Because a variable can be an explanatory variable in one equation but a dependent variable in another equation, we differentiate between 'endogenous' variables and 'exogenous' variables. Exogenous variables are not caused by any other variable in the model. Instead, exogenous variables influence other variables. In a graphical representation of a SEM, no paths (symbolized by arrows) will point towards exogenous variables and paths will only depart from exogenous variables towards other variables. Endogenous variables are influenced by exogenous variables, either directly or indirectly through other endogenous variables (Byrne, 2001; Kline, 2005; Raykov and Marcoulides, 2000). The relationships between exogenous and endogenous variables are represented by the structural model and are defined by the matrices (Hayduk, 1987; Oud and Folmer, 2008):

$$\boldsymbol{\eta} = \mathbf{B}\,\boldsymbol{\eta} + \boldsymbol{\Gamma}\,\boldsymbol{\xi} + \boldsymbol{\zeta} \qquad [1]$$

with $\boldsymbol{\eta}$ = L x 1 matrix of endogenous variables

$\boldsymbol{\xi}$ = K x 1 matrix of exogenous variables

$\mathbf{B}$ = L x L matrix of coefficients of the endogenous variables

$\boldsymbol{\Gamma}$ = K x K matrix of coefficients of the exogenous variables

$\boldsymbol{\zeta}$ = L x 1 matrix of residuals of the endogenous variables

The estimation of a SEM is (usually) based on matching the observed covariances among $\boldsymbol{\eta}$ and $\boldsymbol{\xi}$ with the model-based covariances. In this paper, we used the software package M-plus 4.21 because of its ability to model categorical endogenous variables.

4. Research design

4.1 Study area

For the purpose of addressing the research question how car ownership acts as a mediating variable in the relationship between the built environment and car use, data from the 2000-2001 Ghent Travel Behaviour Survey (Onderzoek Verplaatsingsgedrag (OVG) Gent) were used. The study area comprises the urban region of Ghent which consists of the city of Ghent itself, a medium-sized city in Flanders, Belgium, and the surrounding urbanized villages of Evergem, De

Pinte, Destelbergen, Melle and Merelbeke. In 2000, the total population in this study area was about 315,166 inhabitants and the overall population density was 960.8 inhabitants/km². This is much higher than the average population density in Flanders (439.3 inhabitants/km²) and Belgium (335.4 inhabitant/km²).

4.2 Data source and study sample

The Ghent Travel Behaviour Survey is part of a series of travel surveys in different urban regions in Belgium. Since 1994-1995, the OVG survey is carried out every five years. In every survey, about 2,500 households are asked to participate. The survey yields data on the travel behaviour of approximately 5,500 persons, including children over the age of six. In addition to information on personal and household characteristics, all household members have to complete a trip diary for two consecutive days. This resulted in 39,712 trips reported in the 2000-2001 Ghent Travel Behaviour Survey. However, trips on the second day are reported less correctly (Witlox, 2007; Zwerts and Nuyts, 2001) and, thus, omitted in further analyses. Given that our focus is on the role of car ownership in explaining the relationship between the built environment and car use, the analysis is based on all trips of persons aged 18 years and older. These persons are considered to undertake trips relatively independently. Moreover, the legal age of obtaining a driving licence is 18 years in Belgium. Therefore, persons aged 18 or older have a potentially larger choice set of travel modes than younger persons. We also limited out analysis to short- and medium-distance trips (N = 12,672 trips), since 95% of all trips are undertaken over a distance of up to 60 km. In doing so, we avoid the disturbance of our results by the characteristics of long-distance trips.

4.3 Key variables

Variables used in the analysis include characteristics of the built environment, personal and household characteristics and aspects of car travel behaviour (see Table 1). Built environment characteristics only refer to density, diversity and accessibility; design aspects could not be included in the analysis due to a lack of suitable data.

- The built environment is characterized by (i) built-up index, (ii) land use diversity, (iii) distance to the nearest railway station, (iv) distance to the CBD of Ghent, and (v) accessibility by car. Information on these characteristics is only available for the residence, where most trips depart from. Such information is, however, not always available for the various trip destination locations. The built-up index equals the percentage of built-up surface at the census tract level. It can be considered as a proxy for built-up density. It is derived from the land use database of the Agency of Spatial Information Flanders which offers a categorization between built-up surfaces and open surfaces. Land use diversity quantifies the degree of balance across residences, services and commerce, recreation and tourism, and regional and local industry. Information on these land use types is obtained from regional zoning plans and recalculated at the census tract level in ArcGIS 9.2 according to the equation (Bhat and Gossen, 2004):

$$\text{Land use diversity} = 1-\left(\frac{\left|\frac{r}{T}-\frac{1}{5}\right|+\left|\frac{c}{T}-\frac{1}{5}\right|+\left|\frac{t}{T}-\frac{1}{5}\right|+\left|\frac{i}{T}-\frac{1}{5}\right|+\left|\frac{o}{T}-\frac{1}{5}\right|}{\frac{8}{5}}\right) \qquad [2]$$

with r = km² in residences

c = km² in services and commerce

t = km² in recreation and tourism

i = km² in regional and local industry

o = km² in other land use types

T = r + c + t + i + o

A value of 0 means the land use pattern is exclusively determined by a single land use, whereas a value of 1 indicates a perfect mixing of different land uses. Distance to the nearest railway station is calculated in ArcGIS 9.2 as the shortest path by car along the road network between the residence and the nearest railway station. Distance to the CBD of Ghent is similarly defined. Accessibility by car is defined as the number of people that can be reached by car within 15 minutes[2]. For each residence, accessibility is calculated using the regional travel demand forecasting model Multimodal Model Flanders. It is basically the sum of the number of people of every census tract in the region, weighted by the travel time from the residence to these census tracts. Travel time is calculated in ArcGIS 9.2 as the fastest path by car along the road network. We restricted this travel time to 15 minutes in order to detect differences in local accessibility. After all, our study area has a limited geographical scale so that differences in accessibility are more important on a local level (e.g., within 15 minutes) than a regional level (e.g., within 60 minutes).

[2] We are aware that accessibility is more than just having access to people. Access to facilities such as jobs and shops is important as well. However, we do not focus on a specific travel motive such as working or shopping. Consequently, we could limit our accessibility measure to having access to people and use this measure as a proxy for accessibility in general.

- Personal characteristics include age, possession of a driving licence (0 = yes, 1 = no), marital status (0 = married/cohabiting, 1 = single) and full-time employment (0 = not full-time employed, 1 = full-time employed).
- Household characteristics include monthly household income (three classes) and car ownership (number of cars per household).
- Car use is defined as a binary variable. If a trip is undertaken by car (as a car driver or as a passenger) on the survey day, this variable obtains a value of 1. As a result, car use is a categorical endogenous variable in our analysis. This is no restriction to our analysis since we use the software package M-plus 4.21. As mentioned before, one of the features of this software package is the ability to model categorical endogenous variables.

Almost 12% of all households in our sample do not own a car. Table 1 illustrates that these households have lower incomes compared to households with several cars. Moreover, Table 1 suggests that households with no cars generally reside in densely built neighbourhoods closer to the city centre of Ghent. Surprisingly, these neighbourhoods are not characterized by more land use diversity. Instead, our data suggest that households with several cars live in more diverse neighbourhoods. We suspect that diversity is also associated with higher real estate prices, and rather attract households with higher incomes, and thus more cars.

Table 1. Summary of variables included in the analysis

	no cars N = 261 households	**1 car** N = 1,277 households	**2 or more cars** N = 674 households
Built environment			
built up index	0.75 (0.207)	0.66 (0.246)	0.52 (0.251)
land use diversity	0.15 (0.116)	0.17 (0.114)	0.19 (0.112)
distance to railway station (km)	5.02 (2.338)	6.02 (2.619)	7.53 (2.720)
distance to CBD (km)	3.28 (2.547)	4.25 (3.242)	5.69 (3.574)
accessibility by car, 15 min. (# inhabitants)	94,331 (15,173.8)	94,811 (18,454.0)	92,301 (20,581.0)
Socio-economic and demographic characteristics			
age	53.69 (17.495)	49.43 (15.160)	43.56 (12.190)
driving licence	57.7% no, 42.3% yes	11.5% no, 88.5% yes	2.8% no, 97.2% yes
marital status	32.6% married/cohabiting, 67.4% single	75.0% married/cohabiting, 25.0% single	83.0% married/cohabiting, 17.0% single
monthly household income	91.6% 0-1,859 € 7.7% 1,860-3,099 € 0.8% +3,100 €	58.9% 0-1,859 € 36.0% 1,860-3,099 € 5.1% +3,100 €	14.7% 0-1,859 € 33.4% 1,860-3,099 € 35.7% +3,100 €
full-time employed	64.1% no, 9.8% yes	36.8% no, 63.2% yes	23.4% no, 76.6% yes
Travel behaviour characteristics			
car use	90.2% no, 9.8% yes	36.8% no, 63.2% yes	23.4% no, 76.6% yes

standard deviations are mentioned between parentheses

Note: Non-significant built environment characteristics and other socio-economic and demographic characteristics are not reported in Table 1.

5. A SEM for car use

Having specified the research design and the potential different roles car ownership plays in explaining car use (see Figure 1) we now turn our attention to the modelling results.

5.1 Model specification issues

As in other multivariate techniques, maximum likelihood (ML) method is a generally used estimating procedure in SEM. A basic assumption of this ML-estimator is the multivariate normal distribution of all continuous endogenous variables in the model (Kline, 2005, p. 112). However, in reality this assumption is not always fulfilled. Our models include several not-normally distributed variables and, moreover, our final outcome variable car use is categorical.

An alternative estimator in such circumstances is a mean- and variance-adjusted weighted least square parameter estimator (WLSMV) which we used instead. WLSMV is a robust estimator yielding robust standard errors that does not require extensive computations and does not require enormously lager sample sizes. In addition to robust estimation, a robust mean-adjusted and mean- and variance-adjusted chi-square can be given (Muthén, 1983; Satorra, 1992; Yu and Bentler, 2000).

We have to note that the modelling process consists of two phases. During the first phase, all variables mentioned in Table 1 are included in the models. However, only those variables that significantly influence car ownership and car use are retained in the second modelling phase during which the final models are estimated. Insignificant influences were constrained to be zero.

We also controlled our analysis for the effect of outliers. Commonly used measures to detect outliers are the Mahalanobis distance or the Loglikelihood. However, we could not calculate these measures: the Mahalanobis distance is only available for continuous endogenous variables and the Loglikelihood assumes maximum likelihood estimators. However, M-plus can also calculate Cook's D (Cook, 1977, 1979) and a loglikelihood distance influence measure adjusted for weighted least squares estimators (Cook and Weisberg, 1982) for each observation. These outlier scores were plotted against the scores for car ownership and car use, which are key variables in the model. Doing so, we were able to determine 41 outliers. We removed five outliers at a time and observed the changes in goodness-of-fit indices of the model and individual parameter estimates. Comparable to other studies (e.g., Gao et al., 2008), we found that the χ^2 statistic generally increased after each step of removing outliers. This indicates a worse-fitting model since the χ^2 statistic is the product of the sample size minus one (*N-1*) and the minimized fit function (F_{min}) (Byrne, 2001, p. 78; Kline, 2005, p. 135). A larger χ^2 statistic with a smaller sample size indicates an increase of F_{min}, or in other words a greater discrepancy between the observed covariance matrix and the model-based covariance matrix. Moreover, the means and variances of all variables for the reduced sample are close to the ones of the original sample. After all, 41 outliers on an original sample size of 12,672 observations seem negligible. These findings supported the decision to retain as much information as possible. The results reported in section 5.3 are based on all 12,672 observations.

5.2 Model fit indices

A widely used index to determine model fit is the χ^2-statistic which measures the discrepancy between the observed and model-based covariance matrices. However, χ^2 values increase with sample size and, thus, models based on large sample sizes might be rejected based on their χ^2 value even though small differences exist between the observed and model-based covariance matrices. Nevertheless, it is reported in Table 2 since χ^2 is the basis for other model fit indices (Byrne, 2001; Kline, 2005). Moreover, a dozen of alternative model fit indices are described in the SEM literature in contrast to other multivariate techniques such as linear regression.

Table 2 reports some alternative model fit indices from several different index families. Model fit of the three models generally improves with increasing complexity of the models. However, only the third model obtains a good fit. Only the WRMR-value indicates that the model still can be improved. However, based on the findings of the literature review and the modification indices calculated by M-plus, we could not improve our third model in a theoretically sound way. We suspect that other variables such as attitudes and lifestyles must be accounted for and could improve the modelling results. However, our data source does not contain that kind of information. Therefore, we decided to retain model 3 in its present form.

Table 2. Comparison of some model fit indices for the three models

Model fit indices	**Formula**	**Description**	**Cut-off value**	**Model-based value**		
				Model 1	**Model 2**	**Model 3**
χ^2 (df)	$(N\text{-}1)\ F_{min}$	Measuring the discrepancy between the observed and model-based covariance matrices. χ^2 dependents on sample size. Smaller values indicate better model fit.	$p > 0.05$	13,530.427 (24) $p = 0.000$	4,196.113 (16) $p = 0.000$	521.171 (13) $p = 0.000$
Error-of-approximation-based indices						
RMSEA (Root Mean Square Error of Approximation)	$\delta = \max(\chi^2 - df, 0)$ RMSEA = $\sqrt{\frac{\delta}{df(N-1)}}$	Measuring the amount of error of approximation per model degree of freedom, while controlling for sample size. Smaller values indicate better model fit.	< 0.05	0.21	0.14	0.05
Residual-based fit indices						
WRMR (Weighted Root Mean Square Residual)	$\sqrt{\sum_r^e \frac{(s_r - \hat{\sigma}_r)/v_r}{e}}$ where e is the number of sample statistics, s_r and $\hat{\sigma}_r$ are elements of the sample statistics and model-estimated vectors, respectively, v_r is an estimate of the asymptotic variance of s_r	Measuring the weighted average differences between the observed and estimated variances and covariances.	< 1.00	21.58	11.18	3.89
Measures of comparative fit to a baseline model						
CFI (Comparative Fit Index)	$1 - \frac{\delta_M}{\delta_B}$	Assessing the improvement of the hypothesized model M compared to the independence model B with unrelated variables.	> 0.90	0.07	0.71	0.97

TLI (Tucker-Lewis Index)	$\dfrac{\dfrac{\chi_B^2}{df_B} - \dfrac{\chi_M^2}{df_M}}{\dfrac{\chi_B^2}{df_B} - 1}$	Assessing the improvement of the hypothesized model M compared to the independence model B with unrelated variables.	> 0.90	-0.05	0.51	0.93

Byrne, 2001; Hu and Bentler, 1999; Kline, 2005; Yu, 1999.

The model fit of each model separately indicates that model 3 is an improvement over model 2 and model 1. This is also confirmed by a χ^2 difference. The models are hierarchically nested into each other so that comparing the χ^2 values is possible. The χ^2 difference test suggests that model 2 is an improvement over model 1 ($\chi^2\Delta$ = 9,676.238, df = 8, p = 0.000), and model 3 over model 2 ($\chi^2\Delta$ = 6,459.387, df = 7, p = 0.000). Or in other words, defining car ownership as a mediating variable while partly controlling for residential self-selection adds explanatory power to the models. Model 3 is, therefore, retained for further discussion.

5.3 Direct, indirect and total effects

Prior to discussing the results of model 3, we determine the consequences of ignoring car ownership as a mediating variable by comparing the results of model 1, model 2 and model 3. Table 3 reports unstandardized as well as standardized total effects. Unstandardized total effects point out the direction and the significance of the relationship between the built environment, and car ownership and car use, whereas standardized total effects illustrate the strength of this relationship. According to our findings, ignoring the effects of residential self-selection and/or car ownership as a mediating variable might result in a misspecification of the effects of the built environment. While partly controlling for the effects of residential self-selection model 2 did not consider car ownership as a mediating variable. Two built environment characteristics, the distance between the residence and the nearest railway station as well as car accessibility, obtain larger unstandardized total effects. Moreover, their standardized total effects are somewhat larger than in model 3, indicating a more important influence compared to other variables. Ignoring car ownership as a mediating variable can also lead to non-significant effects of the built environment. The significant effects in model 3 of land use diversity and distance between the residence and the CBD of Ghent disappear in model 2. Only the built-up index seems to maintain a similar effect. This is also the case in the first model which does not account for residential self-selection and car ownership as a mediating variable. All built environment characteristics, except the built-up index, have an insignificant effect on car use in model 1. The effect of car ownership itself on car use might also be somewhat overestimated if results of model 1 and model 2 are compared to model 3. These findings confirm that, while controlling for residential self-selection, car ownership should be considered as a mediating variable to correctly determine the effects of the built environment on travel behaviour.

Table 3. Comparison of total effects on car use of the three models (significant at α = 0.05)

	Model 1	**Model 2**	**Model 3**
Built environment characteristics			
built up index	-0.781 (-0.173)	-0.611 (-0.134)	-0.699 (-0.155)
land use diversity	-	-	-0.023 (-0.005)
distance to railway station	-	0.517 (0.091)	0.192 (0.034)
distance to CBD	-	-	0.077 (0.013)
accessibility by car, 15 min.	-	0.391 (0.065)	0.153 (0.026)
Socio-economic and demographic characteristics			
age	-0.360 (-0.065)	-0.361 (-0.064)	-0.356 (-0.064)
no driving licence	-1.008 (-0.277)	-1.010 (-0.274)	-0.996 (-0.272)
marital status, single	-0.285 (-0.112)	-0.286 (-0.110)	-0.282 (-0.110)
household income, 0-1,859 € (ref. cat.)			
household income, 1,860-3,099 €	-	0.089 (0.039)	0.159 (0.071)
household income, + 3,100 €	-	0.154 (0.053)	0.376 (0.129)
full-time employed	0.062 (0.028)	0.062 (0.028)	0.061 (0.027)
car ownership	2.968 (0.234)	2.974 (0.231)	2.350 (0.224)

- = no significant effect defined, unstandardized coefficients are mentioned without parentheses, standardized coefficients are mentioned between parentheses

Subsequent to determining model fit, the significance of every single parameter in model 3 is tested. We controlled our results for the issue of residential self-selection by estimating the effect of income on the built environment characteristics (see Table 4). Based on our data, higher incomes are associated with living in less densely built and more diverse neighbourhoods. These neighbourhoods have good car accessibility, but are also located further away from the CBD of Ghent and the nearest railway station. Doing so, the results are partly controlled for residential self-selection.

Table 4 reports the direct, indirect and total effects on car ownership and car use. According to the unstandardized total effects, car ownership is lower among people living in densely built and diverse neighbourhoods as expected. The same seems to hold for distance to the nearest railway station and distance to the CBD of Ghent. On the other hand, residing in neighbourhoods with good car accessibility might encourage car ownership. This indicates that the built environment can have the presumed effect on car ownership. All socio-economic and demographic variables have the expected effect on car ownership. Car ownership is positively related to household income, and it is negatively related to age, not owning a driving licence and being single. Nevertheless, other variables, such as full-time employment, gender, education and the presence of young children, are not significant and, therefore, not reported in Table 3.

Table 4. Direct, indirect and total effects on car ownership and car use (significant at $\alpha = 0.05$)

	BUILT UP INDEX ($R^2 = 1.8\%$)		
	Direct effect	**Indirect effect**	**Total effect**
household income, 0-1,859 € (ref. cat.)			
household income, 1,860-3,099 €	-0.039 (-0.077)	-	-0.039 (-0.077)
household income, + 3,100 €	-0.095 (-0.148)	-	-0.095 (-0.148)
	LAND USE DIVERSITY ($R^2 = 0.4\%$)		
	Direct effect	**Indirect effect**	**Total effect**
household income, 0-1,859 € (ref. cat.)			
household income, 1,860-3,099 €	0.016 (0.034)	-	0.016 (0.034)
household income, + 3,100 €	0.040 (0.066)	-	0.040 (0.066)
	DISTANCE TO RAILWAY STATION ($R^2 = 0.1\%$)		

	Direct effect	Indirect effect	Total effect
household income, 0-1,859 € (ref. cat.)			
household income, 1,860-3,099 €	0.011 (0.027)	-	0.011 (0.027)
household income, + 3,100 €	0.013 (0.025)	-	0.013 (0.025)
	DISTANCE TO CBD (R^2 = 0.9%)		
	Direct effect	**Indirect effect**	**Total effect**
household income, 0-1,859 € (ref. cat.)			
household income, 1,860-3,099 €	0.024 (0.062)	-	0.024 (0.062)
household income, + 3,100 €	0.050 (0.102)	-	0.050 (0.102)
	ACCESSIBILITY BY CAR, 15 MIN. (R^2 = 0.1%)		
	Direct effect	**Indirect effect**	**Total effect**
household income, 0-1,859 € (ref. cat.)			
household income, 1,860-3,099 €	-	-	-
household income, + 3,100 €	0.017 (0.034)	-	0.017 (0.034)
	CAR OWNERSHIP (R^2 = 37.3%)		
	Direct effect	**Indirect effect**	**Total effect**
Built environment characteristics			
built up index	-0.038 (-0.088)	-	-0.038 (-0.088)
land use diversity	-0.010 (-0.022)	-	-0.010 (-0.022)
distance to railway station	0.082 (0.151)	-	0.082 (0.151)
distance to CBD	0.033 (0.058)	-	0.033 (0.058)
accessibility by car, 15 min.	0.065 (0.115)	-	0.065 (0.115)
Socio-economic and demographic characteristics			
age	-0.026 (-0.049)	-	-0.026 (-0.049)
no driving licence	-0.076 (-0.219)	-	-0.076 (-0.219)
marital status, single	-0.020 (-0.080)	-	-0.020 (-0.080)
household income, 0-1,859 € (ref. cat.)			
household income, 1,860-3,099 €	0.055 (0.255)	0.003 (0.014)	0.055 (0.269)
household income, + 3,100 €	0.128 (0.463)	0.007 (0.025)	0.128 (0.488)
	CAR USE (R^2 = 20.1%)		
	Direct effect	**Indirect effect**	**Total effect**
Built environment characteristics			
built up index	-0.610 (-0.135)	-0.089 (-0.020)	-0.699 (-0.155)
land use diversity	-	-0.023 (-0.005)	-0.023 (-0.005)
distance to railway station	-	0.192 (0.034)	0.192 (0.034)
distance to CBD	-	0.077 (0.013)	0.077 (0.013)
accessibility by car, 15 min.	-	0.153 (0.026)	0.153 (0.026)
Socio-economic and demographic characteristics			
age	-0.294 (-0.053)	-0.062 (-0.011)	-0.356 (-0.064)
no driving licence	-0.817 (-0.223)	-0.180 (-0.049)	-0.996 (-0.272)
marital status, single	-0.236 (-0.092)	-0.046 (-0.018)	-0.282 (-0.110)
household income, 0-1,859 € (ref. cat.)			
household income, 1,860-3,099 €	-	0.159 (0.071)	0.159 (0.071)
household income, + 3,100 €	-	0.376 (0.129)	0.376 (0.129)
full-time employed	0.061 (0.027)	-	0.061 (0.027)
car ownership	2.350 (0.224)	-	2.350 (0.224)

- = no significant effect defined, unstandardized coefficients are mentioned without parentheses, standardized coefficients are mentioned between parentheses

Comparable conclusions can be drawn for car use. Unstandardized total effects indicate that people living in a highly built and mixed use neighbourhood are less likely to use a car on the survey day. Both spatial aspects have the expected and significant effect on car use. Moreover, based on our data car use is also likely to be lower among people residing in neighbourhoods close to a railway station and the CBD of Ghent. However, car use is likely to be higher in neighbourhoods with good car accessibility. Car use is positively related to monthly household income, being full-time employed and car ownership. On the other hand, our results suggest that older people and people not owning a driving licence or being single are less likely to use a car on the survey day. It is important to base these conclusions on the total effects. Total effects are the sum of direct and indirect effects. Whereas other studies sometimes find opposing direct and indirect effects (e.g., Gao et al., 2008; Van Acker and Witlox, 2009), all variables with a direct as well as an indirect influence have synergistic effects resulting in even larger total effects. However, focusing on direct effects only would lead to inconsistent conclusions in some cases. For example, our data suggests that most built environment characteristics are not significantly associated with car use if one should only focus on direct effects. However, car use is likely to be influenced by the built environment but mainly in an indirect way through the interaction with car ownership. This finding could give us the impression that car ownership is only a substitution of the built environment. However, the built-up index has a significant direct effect on car use. This suggests that car ownership replaces the influence of some but not all built environment characteristics. Another example relates to the influence of income on car use. It is believed that middle and high income families can afford to own (several) cars and to travel more by car. However, the direct effect of monthly household income on car use is not significant. It is only through the indirect effect, caused by the interaction between car ownership and car use, that the total effect is significant. This indicates that car mobility of high income groups is not necessarily caused by their higher incomes but rather by their higher car ownership.

Based on the standardized total effects (reported between parentheses in Table 3), variables can be distinguished that determine car ownership and car use to a large extent. It seems that car ownership is mainly influenced by monthly household income and owning a driving licence. However, our data also suggests an important influence of the built environment on car ownership, especially car accessibility and the distance between the residence and the nearest railway station. The effect of the built environment is, however, less pronounced for car use than for car ownership. Only the built-up index has a considerable effect on car use, other socio-economic and demographic variables such as owning a driving licence are more important. The standardized direct effect also suggests a clear relationship between car ownership and car use. Hence, our analysis points out that the effect of the built environment on car use primarily exists through the mediating variable car ownership.

6. Conclusion

So far, empirical studies on travel behaviour consider car ownership either as an aspect of travel behaviour that has to be explained or as a variable that explains other aspects of travel behaviour (e.g., car use, travel distance, etc.). This paper aimed at combining both approaches and deducing the meaning of car ownership as a mediating variable.

Since car ownership is considered as an explanatory and a dependent variable at the same time, statistical techniques such as regression analysis are no longer suitable. Structural equation modelling is a more advanced modelling technique that can be used to disentangle the complexity of travel behaviour. Within this paper, a structural equation model (SEM) is used to estimate the relationships between the built environment, car ownership and car use.

SEM is a confirmatory method; hence, the modelling process has to be guided by a conceptual model and hypotheses. By comparing the overall fit of three models, we found that car ownership likely mediates the relationship between the built environment and car use. The interpretation of the modelling results also confirmed car ownership as a mediating variable. For example, some studies (e.g., Dargay and Hanly, 2004; Kockelman, 1997; Schwanen et al., 2002) assume a direct effect of income on car use. However, with our definition of car use as a binary variable in mind, our analysis indicated that the income effect on car use probably exists only through car ownership. Thus, car use seems to be influenced only indirectly by income. Nevertheless, direct effects of income remain possible on other aspects of travel behaviour. For example, higher incomes probably do significantly contribute to higher distances travelled. Moreover, ignoring car ownership as a mediating variable is likely to result in a misspecification of the effects of the built environment: the effect of some built environment characteristics on car use might be overestimated. This indicates that car ownership should be considered as a mediating variable in order to correctly determine the usefulness of urban planning policies which intend to discourage car use.

Comparing our findings with modelling results from other studies on the relationship between the built environment and travel behaviour points out that our model explain a relatively large proportion of variance in car use ($R^2 = 20.1\%$)[3]. However, it also indicates that other variables must be taken into account to fully understand car travel behaviour. Some studies (e.g., Bagley and Mokhtarian, 2002; Schwanen and Mokhtarian, 2005a, b; Van Acker et al., 2009) suggest that socio-psychological characteristics, such as lifestyle, perceptions, attitudes and preferences, may add explanatory power.

[3] We have to note that with a dichotomous outcome variable, the reported explained proportion of variance is actually the variance in the underlying continuous latent variable for which the binary car use variable is the observed manifestation, and not the variance in the observed car use variable itself.

Our analysis does however offer some insights which support the importance of the built environment. Unlike the findings of other studies (e.g. Dieleman et al., 2002; Schwanen et al., 2004; Simma and Axhausen, 2003), we found that lower car ownership and less car use is associated with living in high density and mixed use neighbourhoods which have poor car accessibility and are located close to the CBD of Ghent or a railway station. Although the unstandardized model results point out a desired effect of the built environment on car use, the standardized results indicate that this relationship is weak. Other variables, especially car ownership, influence car use to a greater extent. This suggests that urban planning policies should not only focus on influencing car use directly by measures of increasing density and diversity, but also on indirect measures through car ownership. Once people own a car, they tend to use it more often. Besides making cars directly more expensive to own and operate, i.e. through registration fees, gasoline taxes and road pricing, our results suggest that urban planning policies can apply measures of increasing density and diversity in order to discourage car ownership (Boussauw and Witlox, 2009). In this way, urban planning policies are likely to influence car travel behaviour.

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