Subjective Measure of Car Dependence

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A subjective measure of car dependence was developed on the basis of people's own assessment of their reliance on car use. The measure supplements the commonly used objective measure on the basis of actual car use. Structural equation models (SEMs) were estimated to quantify the subjective dependence and to examine its determinants: demographics, socioeconomics, and land use and transit access. The comparison between subjective dependence and actual car use disclosed significant differences between the measures, despite their statistical linkage. The measures also differed significantly in terms of how they were influenced by the determinants. Segmenting the population by both measures revealed 20% of the sample with contrasting subjective and objective measures. After controlling for the determinants, the SEMs examined relations between subjective car dependence (attitude), actual car use (behavior), and the intent to reduce car use (intention). Given the cross-sectional nature of the data, causality could not be proven. Two plausible structural relationships were tested: that actual car use determined subjective car dependence and that no direction of causality was assumed. Subjective car dependence mediates the impact of car use on the intent to reduce it: the direct effect of car use on the intent to reduce it is 0.2; the indirect effect through stated car dependence is −0.6; the total effect is −0.4. Actual car use explains approximately 50% of the variation in subjective car dependence, which, together with actual car use, explains approximately 60% of the variation in people's intent to reduce car use.

Since Goodwin made the distinction between car-dependent people and car-dependent trips in his 1995 editorial to *Transport Policy* (*1*), the term "car dependence" has been generalized to have a wide range of connotations: from trips and people to activities and communities and to the society at large. [See Lucas (*2*) for a summary of the terminologies related to car dependence in the literature.] Different definitions require different measurements. Stradling distinguished ways of measuring car-dependent places, persons, and trips (*3*). Here, the term refers to car dependent people and focuses on its corresponding measurements.

The extent to which a person is dependent on a car can be assessed by several indicators, including the absolute ones (e.g., how much a person uses the car) and the relative ones (e.g., what portion of the total travel is done by car). Both sets of indicators can be in the units of the number of car journeys, time spent traveling by car, and distance traveled by car (*3*). Both are objective measures of car dependence based completely on car use.

However, Goodwin rejected the notion that car dependence is simply synonymous with the amount of use (*4*). A more sophisticated measure was proposed by Zhang, who interpreted car dependence from individuals' mode choice perspective and quantified car dependence as the extent to which other travel options are excluded from the considered choice set (*5*).

This paper makes the distinction between objective car use behavior and psychological state of feeling dependent on cars and proposes a subjective measure of car dependence based on people's own assessment of their reliance on cars, which supplements the commonly used objective measure. The paper aims to examine three questions:

1. What are the determinants of subjective car dependence? Three categories of variables were examined, including demographic characteristics such as age, gender, and family structure; socioeconomic status, such as income and employment status; and land use patterns, such as population density, land use mixture, and access to transit services (*6–8*).
2. How does the subjective measure compare with the objective measure?
3. What are the relations between subjective car dependence (attitude), actual car use (behavior), and intent to reduce car use (intention)?

SUBJECTIVE CAR DEPENDENCE

Data

The main data source is the Londoners' Lifestyle and Car Dependence Survey carried out by Transport for London between 2005 and 2006 (*9*). It was a web-based survey supplemented by face-to-face interviews with people aged 65 or older. A total of 1,330 individuals were included as the study sample after removing those who lived outside greater London, inconsistent records, and records with missing values. The response rate was 60%, higher than typical response rates for online surveys, thanks to sending out reminder e-mails after the initial solicitation. In addition to the typical socioeconomic (Table 1) and travel behavior variables, the survey contained 102 Likert scale psychometric indicators, including statements on attitudes, personality, and lifestyle. Each statement had five response levels: strongly agree, slightly agree, neither agree nor disagree, slightly disagree, and strongly disagree, which were coded as 2, 1, 0, –1 and –2, respectively.

Subjective car dependence and intent to reduce car use were measured as latent variables DEPEND and INTENT, respectively, by indicators shown in Table 2. Three indictors were used to quantify people's subjective car dependence: indicator i1 offers an overall assessment (approximately 40% of the people think their lifestyles depend on having a car); indicator i2 probes from the perspective of whether other travel modes are considered in the choice set (close to 30% of people do not think there needs to be a decision-making process at all); and indicator i3 asks about the possibility of change (more than half of the people feel they do not have practical alternatives). Two statements were used to quantify people's intent

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TABLE 1 Socioeconomic Background of the Sample

Variable	Values	Percentage
Demographic		
Age (years)	≤54	91
	55+	9
Gender	Male	46
	Female	54
Ethnicity	British	67
	Other	33
No. of adults in the household	1	20
	2	52
	3+	28
Having children	Yes	35
	No	65
Socioeconomic		
Employment	Employed	79
	Other	21
Social grade	A, B	51
	C1, C2	38
	D, E	11
Income (£ thousands)	Low (<15)	13
	Middle (15–30)	43
	High (>30)	44
Land Use and Public Transit Access		
Location	Outer London	67
	Inner London	30
	Central London	3
Population density	Low	34
	Middle	40
	High	26
Public transit access	Low	31
	Middle	53
	High	16

[a]£1 = $1.60 in 2011.

to reduce car use: close to half of the people stated that they were actively trying to use cars less, and close to one-third expressed interest in reducing their car use.

It is important to examine whether the chosen indicators can reliably measure the underlying latent constructs DEPEND and INTENT. The coefficient of reliability, Cronbach's alpha, is commonly used to measure the internal consistency. The results of 0.730 and 0.632 for DEPEND and INTENT, respectively, are above the commonly accepted threshold of 0.6 to approximately 0.7 (*10*). A simple average of the indicators was used as the initial values for DEPEND and INTENT to explore their relationship with people's demographics, socioeconomics, and land use and transit access. Later in the structural equation models (SEMs), factor scores were recalculated on the basis of the measurement equations. Both factors were normalized to have a mean of 0 and a standard deviation of 1.

The survey reported individual's trip frequency in general by each mode: car as driver, car as passenger, bus, underground, national rail, walking, bicycling, and others. Car as driver and car as passenger were combined into one category. The frequencies were reported as ranging from 7 days a week, 6 days a week, and so forth to once in 6 months, which were converted to trips per day to calculate trip frequency and mode share as indicators of actual car use, denoted as CARUSE.

Determinants

A series of analyses of variance (ANOVA) procedures was performed to examine whether there were significant differences of subjective car dependence among various demographic and socioeconomic groups or people with different land use and transit access.

Figure 1*a* reports the average level of subjective car dependence by demographic groups. The prominent difference is that people with children depend much more on cars than people without children. British people depend on cars more than non-British people and married couples developed more than the singles do. The formal one-way ANOVA procedures (not reported here but available on request) confirm the significant differences by ethnic group, marriage status, and having children or not at the 5% level. Age and gender are not significant at the 10% level. These bivariate analyses results serve an exploratory purpose only. For example, British people depend on cars more than non-British people, possibly because of their difference in a combination of socioeconomic characteristics, instead of or in addition to their intrinsic cultural differences. This finding becomes clearer in the multivariable analysis in the SEM models: after socioeconomic variables are controlled for, being British no longer plays a significant role in explaining car dependence.

The differences between socioeconomic groups were not as strong. None of the variables was significant at the 5% level. The only significant one at the 10% level was social grade: people in low grade (D, E) feel more dependent on cars than those in the middle (C) or high (A, B) grades. Social grade is a U.K. classification based on occupation developed from the National Readership Survey (*11*). Social grades D and E refer to manual workers, apprentices, state pensioners,

TABLE 2 Indicators of Stated Car Dependence and Intent to Reduce Car Use

ID	Description	Disagree Completely (%)	Disagree Partially (%)	Neither (%)	Agree Partially (%)	Agree Completely (%)	Total (%)
Indicators for DEPEND (Cronbach's alpha = 0.730)							
i1	My lifestyle is dependent on having a car.	20	20	19	29	12	100
i2	I don't have time to think about how I travel. I just get in my car and go.	25	29	17	23	6	100
i3	I would like to reduce my car use, but there are no practical alternatives.	8	15	22	40	15	100
Indicators for INTENT (Cronbach's alpha = 0.632)							
i4	I am actively trying to use my car less.	10	16	26	33	14	100
i5	I am not interested in reducing my car use.	12	29	30	20	9	100

NOTE: ID = identification.

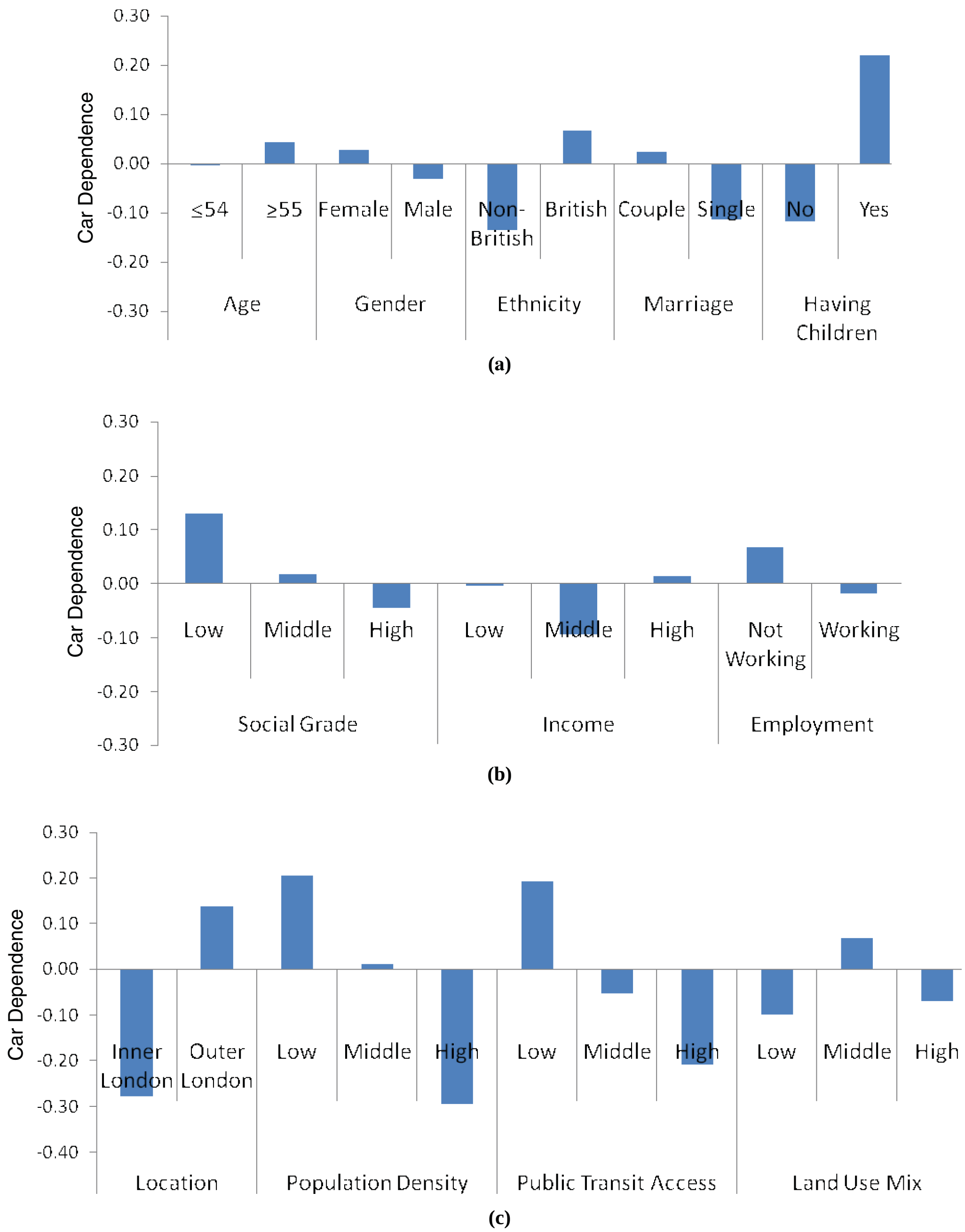

FIGURE 1 Average levels of car dependence by (*a*) demographics, (*b*) socioeconomic status, and (*c*) land use and transit access.

or unemployed. Their higher dependence on car may be because blue-collar jobs are located in areas less well served by public transit compared with Central London, where highly skilled professionals concentrate. Midincome people tend to have lower car dependence than low- and high-income people, but the different is not statistically significant. Neither is the working status significant. Despite the high correlation between social grade, income, and working status, their influences on car dependence are different.

In addition to demographics and socioeconomics, land use patterns and transit access are believed to be important drivers of car dependence (*3–8, 12*). Four variables were included to characterize them:

1. Population density (denoted as density) was calculated at the London ward level in units of people per square kilometer. Each individual was assigned the average population density of the ward where he or she lives. There are 624 wards in Greater London with an average population of 12,000 per ward.
2. Land use data were not available. Instead, the mixture of land use was approximated by the mixture of trips of different purposes. On the basis of the 2001 London Area Travel Survey (*13*), trips that were destined to each of the 624 wards in Greater London were counted by purpose classified by work, leisure and shopping, education, going home, and others. Two variables were developed to measure this mixture. The first was simply the non-going-home proportion of the

trips, approximating the nonresidential land use (denoted as Non-Resi). The second was the entropy of the frequencies of the five trip purposes using the equation

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log_b p(x_i)$$

where $p(x)$ is the proportion of the trips of each of the five trip purposes. The logarithm base b was set to 5 to normalize the value into the range of 0 to 1:0 for no mixture at all (single activity type) and 1 for highest mixture (all trip purposes have equal probability). Both variables were calculated for each ward and an individual is assigned the mixture level of the ward where he or she lives.

3. Home location was a dummy variable OUTERL indicating whether home location was in Outer London.

4. Public transport accessibility level was developed by Transport for London as a measure of the accessibility to the public transportation network in London (*14*), and a ward level average of the public transport accessibility level was used as the indicator of access to public transit.

The land use patterns and transit access variables exhibit strong effects on car dependence. All four variables were significant in the ANOVA test: living in Outer London, lower population density, and poor access to public transit all increased car dependence. The effects of land use mixture variables were not clear: the midlevel mixture showed a higher level of car dependence. This finding sheds some doubt on the way it is approximated by the mixture of trip purposes. In the later multivariate analysis in the SEMs, land use mixture variables turn out to not be significant.

Other factors may influence car dependence as well, such as work location, parking availability and price, road network density, and coverage. These data were not collected and are acknowledged as one of the limitations of the paper.

MODELING CAR DEPENDENCE

Model Structures and Estimations

Given the cross sectional nature of the data set, the paper does not intend to prove causality. Instead, the causal directions between CARUSE, DEPEND, and INTENT were assumed in the model structure, and the survey data were used to quantify the magnitude of these relations. There were at least two plausible hypotheses about the relations between subjective car dependence, actual car use, and intent to reduce car use:

1. CARUSE affects DEPEND, and both affect INTENT. This assumes the causal directions from behavior (actual car use) to attitude (stated car dependence) and from both behavior and attitude to intent. This specification allows us to distinguish direct effect of CARUSE on INTENT from the indirect effect through DEPEND.
2. CARUSE and DEPEND affect each other, and both affect the INTENT. This hypothesis does not specify the causal direction and only examines the association between actual car use and subjective car dependence.

Hypotheses A and B were tested in two models, SEM A and SEM B, respectively, as illustrated in Figure 2.

Both models consist of three sets of equations:

1. Measurement equations that connect latent variables to their corresponding indicators. In addition to DEPEND, measured by indicators i1, i2, and i3, and INTENT, measured by indicators i4 and i5, CARUSE is measured by car trip frequency and car mode share. Although car use is a directly observable quantity, CARUSE is technically treated as a latent variable here to combine both the absolute and relative measures.
2. Structural equations that quantify the impact of demographics, socioeconomics, and land use on each of the three latent variables. The models examined the effect of 13 independent variables, including five demographic, three socioeconomic, and five land use and transit access variables. However, only seven independent variables have a significant impact on at least one latent variable at the 10% level. To reduce clutter on the graph, only significant variables and their connections were drawn, with the standardized coefficient reported on each link.
3. Structural equations that represent the relations among the latent variables. This is where the models differ, corresponding to the differences between Hypotheses A and B.

Both models were estimated in Mplus (*15*) by using the maximum likelihood estimator. The goodness of fit of the model is as follows:

- Observations: 17,000,
- Chi-squared: 193.0,
- Degrees of freedom: 63,
- Comparative fit index: 0.955,
- Tucker Lewis index: 0.921,
- Root mean square error of approximation: 0.039 (with 90% confidence interval of approximately 0.033 to 0.046), and
- Standardized root mean square residual: 0.021.

Both the comparative fit index and the Tucker Lewis index are greater than 0.9 and both the root mean square error of approximation and standardized root mean square residual are less than 0.5 (*16*, *17*). In particular, the entire 90% confidence interval of root mean square error of approximation (0.017 to approximately 0.037) is below 0.5, indicating a strong fit (*18*). Both SEMs have exactly the same goodness of fit, as expected, because they share the same variance–covariance structure, and the only difference is the assumption about the causal directions. The goodness-of-fit statistics does not discriminate between the models (*19*).

Model Results

Table 3 shows the standardized factor loadings and the *t*-statistics for the measurement equations of the three latent variables. All measurement equations are highly significant. This is consistent with the good Cronbach's alpha statistic. Factor scores were calculated using these loading factors and were normalized to have a mean of 0 and a standard deviation of 1, with their distribution shown in Figure 3. The longer tail to the right in DEPEND, indicating a group of high car dependence, matches the left tail in INTENT referring to people who have a weak intention to reduce car use.

The multivariate analysis allows the impacts of the determinants of car dependence to be examined jointly, including demographics,

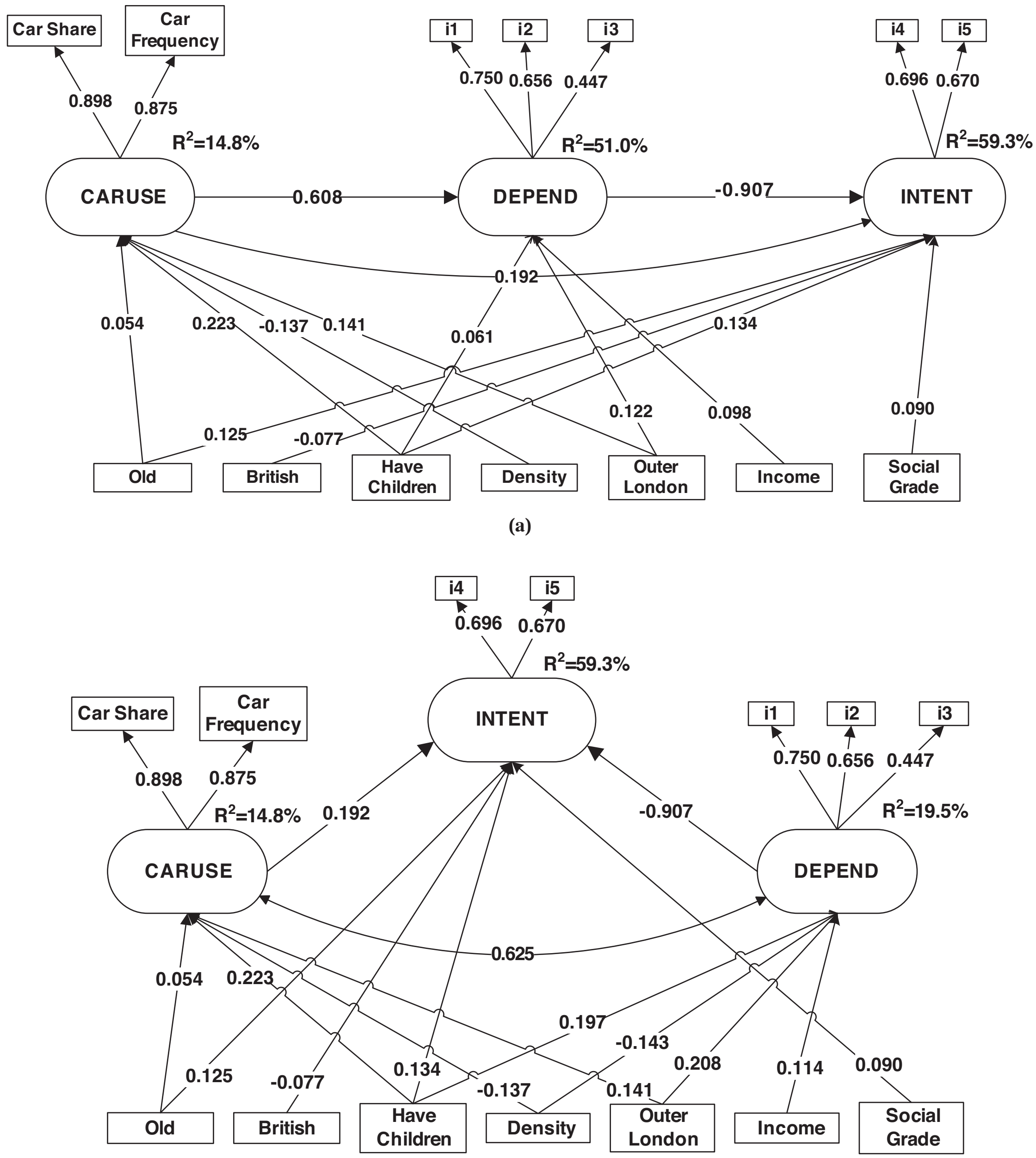

FIGURE 2 Structural equation models (*a*) SEM A and (*b*) SEM B.

socioeconomic status, and land use and transit access. Table 4 reports the structural equations for the determinants of the three latent factors of models SEM A and SEM B. The coefficients for CARUSE are exactly the same for models SEM A and SEM B, so are those for INTENT, as implied by the model specifications. However, the coefficients for DEPEND are different in both models, because in SEM A, CARUSE is also a regressor of DEPEND in addition to demographics and socioeconomics. The coefficients of the observed variables in SEM A should be interpreted as the direct effect on DEPEND after controlling for CARUSE. By contrast, the coefficients in SEM B represent the total effect of the observed variables on DEPEND without controlling for CARUSE. Because subjective car dependence is the focus in this paper, the discussion begins on DEPEND, followed by that on CARUSE and INTENT.

Starting from model SEM B, four of the 13 independent variables were significant for latent variable DEPEND. Of the five demographic variables, only having children was significant and increased the family's reliance on car significantly. Of the three socioeconomic variables, only income turned out to be significant and had a positive impact on car dependence. Of the five land use and transit access variables, higher population density decreases car dependence, and living in Outer London increases it. Neither of the two land use mixture variables nor the transit access was significant, against expectation. All three variables were measured at the Ward level. This may suggest that the impact of land use mix and transit access operate more at the microneighborhood level and require more refined representation. Ward-level averages, combined with the approximation of trip purpose mix for

TABLE 3 Measurement Equations

	Latent Factors					
	f_CARUSE		f_DEPEND		f_INTENT	
Measure	Estimate	Est. SE	Estimate	Est. SE	Estimate	Est. SE
i1	NA		0.750	35.3	NA	
i2	NA		0.656	28.2	NA	
i3	NA		0.447	14.2	NA	
SHCAR	0.898	62.9	NA		NA	
FRCAR	0.875	60.7	NA		NA	
i4	NA		NA		0.696	21.9
i5	NA		NA		0.670	21.3

NOTE: f_CARUSE = factor score of car use; f_DEPEND = factor score of car dependence; f_INTENT = factor score of intent to reduce car use; Est. SE = estimated standard error; SHCAR = car mode share; FRCAR = car trip frequency; NA = not applicable.

land use mix, turned out to be too crude of a measure to provide additional explanatory power to the model, which is a limitation of this research.

The comparison SEM A with SEM B shows that after controlling for CARUSE, the impact of the four variables on DEPEND all diminish: the magnitude of having children, living in Outer London, and income decrease, and density becomes below marginally significant. This finding is reasonable because much of their effects are indirect via CARUSE, which now is being explicitly captured. Take density as an example; SEM B shows that it has a significant negative impact on DEPEND, and SEM A further indicates that density's impact on DEPEND works only through its impact on CARUSE.

Comparing the effects of the observed variables on actual car use and on subjective car dependence reveals interesting similarities and contrasts. Three independent variables affect both car use and car dependence in a similar way: having children, lower population density, and living in Outer London all increase both people's mental state of feeling car dependent and their actual car use. However, two variables behave differently. Being old increases actual car use but does not increase subjective car dependence. Income raises subjective car dependence but not actual car use. The latter is a bit surprising. Perhaps many high-income people in London tend to live in areas with good public transit, but the ward-level average public transport accessibility level in the model does not fully capture the effect of transit access because of the crude geographic unit.

Four observed variables influence INTENT significantly after controlling for CARUSE and DEPEND. Being old increases the intent to reduce car use but increases the actual car use at the same time. This finding is distinct from the general population, who show the opposite directions on CARUSE and INTENT, as will be described shortly. However, this may be reasonable because older people have to use car a great deal even though they would like to reduce its use. Having a higher social grade increases the intent to reduce car use, but it has no effects on actual car use or subjective car dependence. The positive effect of having children on INTENT is worth noting. On the one hand, having children increases both car use and car dependence; on the other hand, after controlling for CARUSE and DEPEND, those who have children would like to reduce car use. Table 5 isolates the direct effect of having children on INTENT from three indirect effects with DEPEND, CARUSE, and CARUSE and DEPEND. Because the direct and indirect effects are in opposite directions and have a similar magnitude, the total effect is minimal. In an auxiliary regression of INTENT against the demographic and socioeconomic variables only, having children is indeed not significant, which hides the complex direct and indirect effects with car use and car dependence. Being British decreases the intent to reduce car use after controlling for other demographic and socioeconomic variables. This finding may indicate cultural differences between the natives and the migrants.

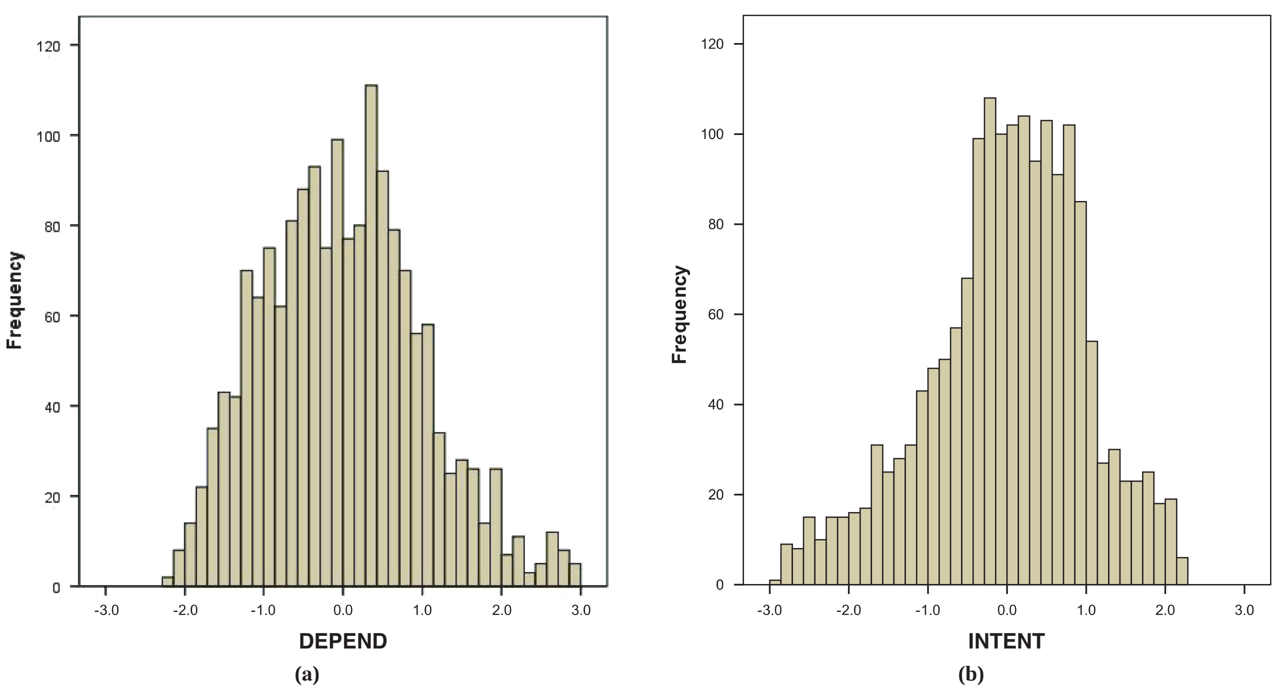

FIGURE 3 Distribution of factor scores of subjective car dependence and intent to reduce car use.

TABLE 4 Structural Equations for the Determinants of Latent Factors

Independent Variable (observed)	Dependent Variables					
	CARUSE		DEPEND		INTENT	
	Estimate	Est. SE	Estimate	Est. SE	Estimate	Est. SE
Model: SEM A						
Old	**0.054**	**1.9**	0.019	0.6	**0.125**	**3.4**
Male	–0.037	–1.3	–0.010	–0.4	–0.018	–0.5
British	0.024	0.8	–0.006	–0.2	**−0.077**	**−2.1**
Single	–0.030	–1.1	–0.007	–0.2	0.026	0.7
Having children	**0.223**	**7.9**	**0.061**	**2.0**	**0.134**	**3.5**
Density	**−0.137**	**−3.7**	–0.060	–1.5	–0.011	–0.2
Entropy	–0.037	–1.0	0.054	1.4	–0.055	–1.1
NonResi	0.003	0.1	–0.014	–0.3	0.021	0.4
Outer London	**0.141**	**4.0**	**0.122**	**3.2**	0.047	1.0
Transit access	–0.035	–1.1	–0.023	–0.6	–0.015	–0.3
Social grade	–0.009	–0.3	–0.044	–1.3	**0.090**	**2.1**
Income	0.026	0.8	**0.098**	**3.0**	0.046	1.2
Working	0.028	0.9	0.010	0.3	0.018	0.5
Model: SEM B						
Old	**0.054**	**1.9**	0.052	1.5	**0.125**	**3.4**
Male	–0.037	–1.3	–0.033	–1.0	–0.018	–0.5
British	0.024	0.8	0.008	0.2	**−0.077**	**−2.1**
Single	–0.030	–1.1	–0.025	–0.8	0.026	0.7
Having children	**0.223**	**7.9**	**0.197**	**5.9**	**0.134**	**3.5**
Density	**−0.137**	**−3.7**	**−0.143**	**−3.2**	–0.011	–0.2
Entropy	–0.037	–1.0	0.032	0.7	–0.055	–1.1
NonResi	0.003	0.1	–0.012	–0.2	0.021	0.4
Outer London	**0.141**	**4.0**	**0.208**	**5.0**	0.047	1.0
Transit access	–0.035	–1.1	–0.044	–1.1	–0.015	–0.3
Social grade	–0.009	–0.3	–0.049	–1.3	**0.090**	**2.1**
Income	0.026	0.8	**0.114**	**3.1**	0.046	1.2
Working	0.028	0.9	0.027	0.7	0.018	0.5

NOTE: Values in bold are statistically significant at 10% level.

However, this difference only exhibits in its effects on the INTENT but not on CARUSE and DEPEND.

Six independent variables do not have any significant impacts on any of the three latent variables:

1. Entropy, NonResi, and transit access. As mentioned earlier, the lack of impact of these variables may be because the ward-level averages do not give enough local geographic details for their impacts to show up.

2. Employment status. Working people usually travel more than others, but London's work trips in general have a higher transit mode share because of the good services to downtown and employment centers such as Canary Wharf. Therefore, the overall trip increases may be offset by the lower car mode share of working trips.

3. Gender and marriage status. Neither was found to be an important determinant for any of the three factors. This finding is consistent with the insignificance of these variables in the bivariate ANOVA.

TABLE 5 Direct and Indirect Effects of Having Children on Intent to Reduce Car Use

Effect	Estimate	Est. SE
Total effect	–0.002	0.0
Direct effect	0.134	3.5
Total indirect effect	–0.136	–4.5
Specific indirect effect		
DEPEND	–0.056	–2.0
CARUSE	0.043	2.6
CARUSE and DEPEND	–0.123	–5.9

Table 6 reports the structural relations between the three latent factors, all of which are significant. As expected, SEM A shows that higher car usage increases subjective car dependence, and feeling dependent on a car decreases the intent to reduce its use substantially. However, after controlling for the subjective car dependence, people who drive a lot have a stronger intent to reduce car use. This finding contrasts with the findings in an auxiliary model where subjective car dependence is not included as an explanatory variable, which reports that people who drive a lot have a lower intent to reduce car use. Table 7 illustrates this finding by analyzing the direct

TABLE 6 Structural Relations Between Latent Factors

Independent Variable or Correlation	Dependent Variable	Estimate	Est. SE
SEM A			
DEPEND	INTENT	–0.907	–11.9
CARUSE	INTENT	0.192	2.7
CARUSE	DEPEND	0.608	20.6
SEM B			
DEPEND	INTENT	–0.907	–11.9
CARUSE	INTENT	0.192	2.7
Correlation between DEPEND and CARUSE	NA	0.625	21.4

and indirect effects of CARUSE on INTENT. Subjective car dependence is an important mediating variable between the actual car use and the intent to reduce it.

When DEPEND and CARUSE are assumed to be correlated without specifying the causal direction, SEM B indicates that the correlation between the subjective and objective measures is indeed strong but far from perfect ($r = .625$). A cross-tabulation in Table 8 by both measures identifies more than 20% of the people whose subjective car dependence and actual car use are opposite. This finding is consistent with the finding by RAC in 1995, which reported that there is a statistical link, but not a close correspondence, between people's report of car dependence and how much they actually drive (*20*).

The R^2-values of the three latent factors in SEM A shows that actual car use explains approximately 50% of the variation in people's subjective car dependence, which, together with car use, explains approximately 60% of the variation in people's intent to reduce car use. SEM B also shows that despite the significant relations between the observed variables and subjective car dependence, the overall R^2 of DEPEND is only 19.5%, suggesting that the capacity of these demographic, socioeconomic, and land use and transit access variables to explain subjective car dependence remains limited.

To demonstrate the model's capacity to explain the intent to reduce car use, two auxiliary SEMs (aux1 and aux2) were estimated, and their R^2-values were compared with that in the main models:

- SEM aux1: model with only demographic, socioeconomic, and land use variables; $R^2 = .08$;
- SEM aux2: aux1 + car use, $R^2 = .19$; and
- SEM A and B: aux2 + subjective car dependence, $R^2 = .593$.

The model with only demographic, socioeconomic, and land use and transit access variables as independent variables can explain only a minimal amount of variation in the intent to reduce car use

TABLE 7 Effects of Car Use on Intent to Reduce Car Use

Effect	Estimate	Est. SE
Total effect	–0.359	–9.0
Direct effect	0.192	2.7
Indirect effect with DEPEND	–0.551	–9.0

TABLE 8 Population Segments Based on Both Car Dependence and Car Use

	Actual Car Use		
Population Segment	Low (%)	High (%)	Total (%)
Stated car dependence			
Low	39.7	10.4	50
High	10.3	39.6	50
Total	50	50	100

8%. Introducing actual car use increases the R^2 to 19%. Adding subjective car dependence in the main models SEM A and B increases the explanatory power substantially to an R^2 of 59.3%.

DISCUSSION OF RESULTS

A new measure is not useful unless it distinguishes itself from other measures and enhances our understanding of the concept in question. This paper concludes with the following reasons that a subjective measure of car dependence is necessary:

1. First, the concept of car dependence refers to both people's actual car use behavior and their psychological state of feeling reliant on a car. The latter connotation requires a corresponding subjective measure.
2. Second, operationally, the availability of psychometric data and factor analysis and SEM methods enable us to quantify the subjective car dependence.
3. Third, the comparison between subjective car dependence and objective car use measures discloses significant differences between the measures despite their statistical link.
4. Fourth, introducing the subjective measure of car dependence greatly enhances the capacity of the model to explain people's intent to reduce car use, which is the immediate antecedent of behavior according to the theory of planned behavior (*21*).

A potential way to characterize car dependence is to regard it as having three aspects: subjective car dependence, actual car use, and intent to reduce car use. The three aspects together provide a fuller picture of car dependence in terms of attitude, behavior, and intention. The models in this paper help reveal how the three aspects are interconnected to each other, but the model results do not rely on this conceptualization. The complexity of car dependence and its measurements echoes the complexity of the motives of car ownership and car use, as the symbolic and affective motives of car use as well as its instrumental motives are identified by many scholars (*12, 22–24*).

The models also examine how the three aspects are affected, sometimes similarly and sometimes differently, by three categories of independent variables. In the demographic category, senior people drive more but also more intend to reduce car use; families with children drive more, feel more dependent on car, and more intend to reduce its use; British people exhibit weaker intent to reduce car use even though they do not behave differently in terms of the actual car use or car dependence. In the socioeconomic category, high-income people feel more reliant on cars, and people with higher social grades express stronger intent to reduce car use but none of them influence the actual car use. In the third category of land use and transit access, lower density and living in Outer London increase both car use and dependence. Land use mixture and transit access are not significant on the basis of this particular data set. None of land use variables affect people's intent to reduce car use.

More questions need to be answered before car dependence can be used to specifically guide transportation policy, such as how car dependence is initially developed and then fully established, to what extent and how it can be influenced and changed, what the effective policy instruments are, what the roles of the broader social and economic contexts are, and so forth. In current modeling practice, latent variables enter the model in the estimation stage but not in the forecasting stage, so they are not policy variables per se. At the same time, the structural equations between observed variables and the latent variables can explain only a limited amount of the variations in the latent variables, as indicated by a low R^2 of 19.5% in this paper and most other papers. This finding suggests that a well-developed substantive theory about these latent variables does not exist. This imposes a great challenge for behavioral studies involving attitudinal factors and prevents them from being used in policy evaluation. Fundamentally to change this situation, latent variables need to become policy variables so that policies targeted at the attitudinal factors can be evaluated. At least two things are required: (*a*) a substantive theory about attitudinal factors describing the principles of the formation and evolution of attitudes, which lay a foundation for the structural equations to be used in forecasting; and (*b*) a history of data set monitoring attitudinal factors and their evolution. It is useful to contrast this finding to the other exogenous variables in the forecast practice. Transportation modelers take the forecast of population or economy from other dedicated agencies or professionals. The only reason that these variables can be forecast is that decades, if not centuries, of data have been cumulated on demographics and macroeconomics based on which patterns can be identified and theories can be developed. As for data on travel-related attitudes, not even a handful of years with consistent variable definition and survey implementation exists. This is a grand challenge and demands a new data infrastructure for transportation studies.

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