European Transport Research Review (2018) 10: 11
https://doi.org/10.1007/s12544-018-0285-9

ORIGINAL PAPER

SEM application to the household travel survey on weekends versus weekdays: the case of Seoul, South Korea

Tae-Hyoung Tommy Gim [1,2]

Received: 6 June 2017 / Accepted: 10 January 2018 / Published online: 17 January 2018
© The Author(s) 2018. This article is an open access publication

Abstract

Purpose This study analyzes the relationship that land use has with weekend travel in comparison to weekday travel. Unlike previous studies, it uses the same sample for two models that are specified to test the relationship separately for weekday and weekend travel.

Methods Structural equation modeling is employed to test the land use–travel relationship. A comparison is made using two mode-specific travel measures: trip frequency and travel time.

Results On weekday travel, land use in Seoul tends to reduce automobile trips and to add transit and nonmotorized trips. This does not lead to a reduction in the total frequency of weekday trips. Instead, an overall reduction occurs in the frequency of weekend trips because the addition of transit and nonmotorized trips is less than the reduction of automobile trips.

Conclusions The application of structural equation modeling to a Seoul household travel survey confirms the opposing role of land use in travel mode choices on weekdays versus weekends.

Keywords Land use · Weekend travel · Trip frequency · Travel time · Structural equation modeling

1 Introduction

Transportation studies have traditionally dealt with weekday travel [1]; relatively few studies on weekend travel have been conducted [2, 3]. However, weekend travel differs markedly from weekday travel in the ranges of destinations and distances as well as the main purposes of travel, modes of transportation, and distributions of peak time [2]. From the late 2000s, studies began to analyze weekend travel and weekday–weekend differences in order to fill this gap [e.g., 4]. However, few studies looked at how weekend travel is related with land use variations, though they have been called for [5, 6]. This topic is increasingly important because urban residents have exhibited a greater tendency to embark on weekend travel in recent years [7, 8], for which trip destinations and lengths vary widely and its purposes tend to be nonmandatory or discretionary (e.g., leisure and social) [6]. Thus, the land use effect on this travel is likely to differ from that on weekday travel [9]. Specifically, land use and transportation planners may be able to intervene if it is found that weekend travel would be responsive to land use interventions [10]. Earlier studies argued that the land use effect is moderate at best [11–14], but these were based mostly on analyses of weekday travel. Also, insomuch as the effect is geographically limited to a local area [15], planners can identify where to intervene considering differences in destinations between nonmandatory weekend travel and mandatory weekday travel [16].

This study analyzes the land use–travel relationship on weekends and examines how it differs from the relationship on weekdays, using a case of Seoul, South Korea. As recommended by previous studies [17, 18], structural equation modeling (SEM) is used to analyze the relationship. Through SEM, the effects of various land use variables are combined to reduce their correlation [e.g., 19]. The correlation between land use independent variables—for example, dense neighborhoods usually have extensive road networks and many transit facilities—is called spatial multicollinearity and requires classical statistical methods such as regression

---

✉ Tae-Hyoung Tommy Gim
taehyoung.gim@snu.ac.kr

[1] Graduate School of Environmental Studies and Interdisciplinary Program in Landscape Architecture, Seoul National University, Gwanak-ro 1, Gwanak-gu, Building 82, Seoul 08826, South Korea

[2] Environmental Planning Institute, Seoul National University, Gwanak-ro 1, Gwanak-gu, Building 220, Seoul 08826, South Korea

analysis to modify (drop or combine) the variables [10]. This makes it difficult to isolate important land use characteristics [20]; it is a major topic for transportation planners and researchers [11, 21]. As shown in the above example, spatial multicollinearity occurs in the examination of both weekday and weekend travel. Despite the collinearity issue, SEM can analyze all land use variables without modification. Furthermore, it allows for multiple relationships in a single model [17]; in this study, land use–travel and sociodemographics–travel relationships are explored.

To deal with spatial collinearity, SEM does not have to transform the original variable set, as it presents the overall effect of a factor through its measurement model, particularly with reflective, as opposed to formative, measurements. In the reflective measurement model, a factor consists of indicator variables that disclose or *reflect* the abstract/latent meaning of the factor. (By contrast, in the case of formative measurement, how indicators are structured entirely determines or *forms* the meaning of a factor. For differences between reflective and formative measurement systems, see Gim [22].) The indicators share the meaning, and the factor is well represented by about three to five of the indicators [23]. In the same sense, the meaning of the factor (content validity) stays intact even if some of the indicators are removed [24]. (In the formative measurement model, however, the addition/removal of an indicator changes the meaning.) Therefore, this study analyzes a few land use indicators and investigates how land use as a whole affects travel behavior [19].

This study attempts to analyze the sociodemographics–travel relationship as a reference for the land use–travel relationship for both weekdays and weekends. Travel modes are categorized three ways: automobile, public transit, and non-motorized modes such as walk and bike. Then, two travel measures are used: trip frequency and (as a composite measure) total travel time. Recognizing a weakness of previous studies that typically used a single measure such as mode choice, unit trip length/time, or total travel distance/time [25], this study uses multiple measures due to Ewing and Cervero's findings [12] that the magnitude of the land use–travel relationship is large when total travel distance (a composite measure) is analyzed, but smaller for analysis of mode choice and smaller still for trip frequency analysis. Thus, this study evaluates variations in total travel time, mode choice, and trip frequency by mode.[1] (Total travel distance is not analyzed due to low data precision.)

The rest of this study is organized as follows. First, it reviews the literature on the land use–weekend travel relationship by categorizing previous studies according to the type of data collected (whether they collected data on weekdays as well as on weekends) and how they considered weekday–weekend differences. Then, it presents research variables and the measurement of the variables with public GIS and travel survey data. The following analysis section provides the results of the weekday and weekend SEM models in terms of factor-to-indicator relationships (findings of the measurement model) and factor-to-factor relationships (findings of the structural model). The study concludes with a summary and interpretation of the findings and recommendations for future research.

2 Literature review

Since the mid-1990s, descriptive research has examined the relationship between land use and travel on weekends as well as on weekdays. For example, Rutherford et al. [26] selected a few neighborhoods in different land use settings and presented their differences using descriptive statistics of such measures as trip length and total travel distance. From the early 2000s, studies began analyzing the land use–weekend travel relationship using inferential statistics. As shown in Table 1, the studies can be categorized into three types, according to how they treated weekday and weekend travel data.

The first type of studies analyzed data that were collected both on weekdays and weekends, but they did not consider weekday–weekend differences in their research model. In order to analyze the land use effect on physical activity, Troped et al. [27] asked research participants to continuously wear a GPS device (accelerometer) for four days or more, including two weekend days. They reported that if ethnicity and educational attainment are controlled for in their linear regression model, density, land use balance, and street intersection density are positively associated with physical activity. In Twin Cities, Minnesota, Forsyth et al. [28] analyzed the effect of residential density on walking (type and amount) and physical activity, each of which was measured with a travel diary and an accelerometer for a week. Using a t-test, they found that housing density is weakly associated with walking and physical activity. Considering that the typical one- or two-day travel diary fails to capture variations in weekend travel and non-regular leisure travel, Gim [33] employed data from a public survey that asked respondents to keep a travel diary for a month. In an SEM model that considered attitudes toward compact land use and different travel modes in addition to sociodemographic variables, land use turned out to significantly influence trip frequency variations. Notably, those studies that used the single model approach looked at weekday and weekend travel at the same time—an improvement from previous weekday-only studies—but, they could not check if these types of travel differed (a strength of the following second group of studies).

---

[1] For a more precise analysis, unit trip time can be examined instead of total travel time. However, because the unit of analysis for this study is the individual, not the trip, an analysis of trip time—often in the form of the *mean* trip time of the individual—is likely to lower the accuracy of the analysis.

Table 1 Studies on weekday–weekend travel

Methods (characteristics)	Authors (years)	Conclusions
A single model without a weekday–weekend difference dummy (analytical findings in relation to the significance of the land use effect can be applied both to weekday and weekend travel)	Troped et al. (2010) [27]	Density, land use balance, and street intersection density increase physical activity.
	Forsyth et al. (2007) [28]	Housing density is positively associated with walking and physical activity.
	Gim (2011) [9]	Compact land use facilitates automobile alternative travel.
A single model with a weekday–weekend difference dummy (it was tested and confirmed that the difference dummy has a significant effect on travel behavior)	Cervero and Duncan (2003) [29]	The weekend dummy positively affects walking and biking; land use diversity and design increase them.
	Ogilvie et al. (2008) [30]	The weekend dummy works negatively on active travel and positively on physical activities; land use has a limited effect on them.
Two separate weekday and weekend models (it was found that different land use variables may be significant in the weekday and weekend models)	Lee et al. (2009) [4]	Residential density and rail proximity reduce the total travel time on weekdays, but not on weekends.
	Lin and Yu (2011) [31]	Residential land use affects children's leisure travel both on weekdays and weekends.
	Witten et al. (2012) [32]	Neighborhood land use increases leisure-purpose physical activities on weekdays and weekends.

Second, several studies considered the weekday–weekend difference by including it as a dummy variable in research models. For example, Cervero and Duncan [29] analyzed the data of the 2000 Bay Area Travel Survey. Different from Bhat and Gossen [2] and Bhat and Srinivasan [34] who analyzed the same data, they used the longitudinal data of the same respondents for both days for which data were available, rather than just one weekend day. Their binomial logistic regression models treated whether a trip was made on the weekday or the weekend as a travel characteristic variable along with four other binary variables relating to travel purposes. In addition to the trip characteristics, sociodemographics—gender, race, and numbers of vehicles and bikes owned—were controlled for. Two mode-specific models found that walking and biking are more likely to occur on weekends and that the factors of land use diversity and design have modest effects on walking and biking. The sociodemographic control variables had far greater effects, and the researchers argued that designing the built environment in line with the sociodemographic composition of a neighborhood could increase physical activity levels through the process of residential self-selection. Similarly, using survey data that were collected from the same respondents for multiple days in impoverished neighborhoods in Glasgow, Scotland, Ogilvie et al. [30] analyzed how active travel and physical activities are associated with individual and environmental variables while controlling for the day of the week (weekday/weekend dummy). In their multinomial logistic regression model in which age, body mass index, housing tenure, distance to work/school, bike access, automobile access, and difficulty walking were controlled for, weekday time was shown to increase the chance of active travel. Physical activities, however, were more likely to be on the weekend. Land use characteristics turned out to have a limited effect on physical activity and active travel. All in all, studies of this type found that the binary variable of the weekday–weekend difference has a significant effect on travel behavior. They did not, however, explain which characteristics that diverge between weekdays and weekends bring about travel variations.

Thirdly, a few studies analyzed the effect of land use on weekday and weekend travel in respective weekday and weekend models; these studies provide a basis for this study. Lee et al. [4] analyzed household travel data from the SMARTRAQ (Strategies for Metropolitan Atlanta's Regional Transportation and Air Quality) survey to check the effect land use might have on total travel time. The effect was estimated in two Tobit models, one for weekday and the other for weekend travel. The researchers controlled for household and individual sociodemographics (children, household size, automobiles, age, gender, and job type). The two models delivered different results: The reduction in total travel time was affected by land use (particularly, residential density and rail proximity) on weekdays, but not on weekends. [Unlike other studies that used weekday–weekend separate models (to be shown below), Lee et al. [4] evaluated travel time in total, not travel time during leisure time only, as with this particular study.] Compared to their study, first, this study does not exclude collinear variables, but keeps all of them; they are loaded onto the land use factor through the measurement model of SEM. Second, in addition to total travel time, this study analyzes variations in trip frequency and further, both of the travel time and trip frequency measures are examined for three modes of travel. Finally, while Lee et al. [4] used a dataset from a pseudo panel (i.e., different sets of individuals were used for the weekday and weekend travel models), this study employs the same sample of respondents to test the weekday and weekend models; if two different samples are analyzed, one can hardly separate variations due to the weekday–weekend difference from the total variations (= weekday–weekend variations + between-sample variations).

By collecting multi-day data from the same elementary school students enrolled in three institutions in Taipei, Taiwan, Lin and Yu [31] investigated how land use in residential areas affects children's leisure travel. Negative binomial regression and multinomial logistic regression were employed to evaluate the students' weekday and weekend travel. The weekday and weekend models both controlled for neighborhood safety (satisfaction level and number of crimes), trust in neighbors, income, automobile/motorcycle/bike ownership, number of children, flexible work type, gender, and school grade. In contrast to Lin and Yu's study, this study concentrates not on the individual effects of land use variables, but on the overall land use effect in order to present its magnitude, not just the statistical significance and direction (+/−). Lastly, Witten et al. [32] analyzed how land use influences physical activities for leisure (not for travel) in 48 New Zealand neighborhoods. To measure such physical activities, they conducted a survey in which *perceived* travel time, leisure time, and walking time were answered. As an *objective* supplement, respondents were also asked to wear an accelerometer for seven consecutive days. The objective accelerometer counts were analyzed separately in weekday and weekend multiple linear regression models in which the authors controlled for age, ethnicity, gender, education, marriage, income, employment, automobile access, and preference for walkable neighborhoods. However, the study focused on differences between perceived/responded physical activities and objectively measured ones, not those between weekday and weekend activities (indeed, their correlation was moderately high and weekday and weekend activities were considered equivalent).

In summary, inferential analyses of multiple-day travel data can be divided into three types of modeling approaches: (1) a single model without a weekday–weekend difference dummy, (2) a model with such a dummy, and (3) separate weekday and weekend models. In contrast to weekday- or weekend-only studies, analytical results of the first type of studies may represent both weekday and weekend travel, but they cannot show whether the travel differs between weekdays and weekends. The second type of studies tests the significance of the weekday–weekend difference, but they cannot determine what brings about such a difference, if the difference is significant; this can only be disclosed by the third type of studies. This study is also classified into the third type, but differs from the previous literature in that it does not exclude initially considered land use variables due to spatial multicollinearity (accordingly, it is capable of examining the magnitude of the land use effect as a whole), analyzes multiple travel measures (trip frequencies and travel time) by travel mode, and uses data from the same sample of respondents for its weekday and weekend travel models that account for an individual's different travel purposes, not limited to leisure travel.[2]

Lastly, while this study reviewed the few studies that analyzed both weekday and weekend travel, the studies—as well as studies only on weekend travel [e.g., 2, 34, 35]—did not adopt SEM, despite the fact that it has been consistently recommended for analyses of the complex land use–travel relationship [17, 18] and indeed, it is often employed in weekday travel studies [e.g., 19, 36–38]. All of the above studies used linear and/or logistic regression, except in two cases: Forsyth et al. [28] used a t-test and Lee et al. [4] used Tobit models. That is, this study is among the first that employed SEM to compare weekday and weekend travel.

3 Data

The study area of this study is Seoul (known officially as Seoul Special City), the capital of South Korea, where individuals' travel and sociodemographic data were obtained from the 2006 Capital Region Household Travel Survey (CRHTS). The survey was conducted in Seoul and its surrounding areas, Incheon Metropolitan City and Gyeonggi Province.

The 2006 CRHTS is an extension of the 1996 Seoul Transportation Census and the 2001 Seoul Household Travel Survey, both of which were carried out only in Seoul. As stipulated by the National Transport System Efficiency Promotion Act, the survey is conducted every five years, and it has been extensively used in previous studies on the land use–travel relationship [e.g., 39–44]. However, none of them used the data of its supplementary weekend survey partially because they have not been publicly available, unlike the data of the main weekday survey.

The supplementary weekend survey was not conducted by the CRHTS until 2006. Thus, the 2006 CRHTS was the first to include not only the main weekday survey (it asked respondents to keep a travel diary on the last Thursday of October or the first Thursday of November 2006), but also a weekend survey (on the following Saturday and Sunday). Notably, the CRHTS did not comprise a sample from the whole year. Rather, it examined one-day trips for the weekday main survey and two-day trips for the weekend supplementary

---

[2] Except Gim [33] and Witten et al. [32] whose analytical models included neighborhood and/or travel mode preference variables, no other studies on weekday and weekend travel, including this one, did not duly control for residential self-selection by considering attitudinal variables and/or analytical methods that can deal with this issue, including sample selection model or propensity score matching. Thus, as suggested by previous weekday and weekend travel studies like Forsyth et al. [28], Cervero and Duncan [29], and Lee et al. [4], further study is required to address the self-selection issue.

survey; this may limit the generalizibility of the findings of this study.

The CRHTS had a form of a self-administered (pen-and-pencil) survey—questionnaires were hand delivered and retrieved by block group heads—but as an additional measure, interviews were also conducted by phone and personal visit. Accordingly, both the weekday and weekend surveys achieved very high response rates: 94.1% (= 95,698 returned responses) and 100% (= 5102), respectively.[3]

Unlike the 2011 and 2016 National Household Travel Surveys, the 2006 CRHTS assigned the same format of the IDs to the two weekday and weekend samples, so this study was capable of extracting the respondents who answered both of the weekday and weekend surveys. As such, by using the same sample for its weekday and weekend models, this study can directly compare their analytical results. From the combined sample, it excluded one case whose gender was missing and came up with a final sample of 1960 Seoul residents. Figure 1 shows how the sample is distributed on the neighborhood scale.

Based on the data of the 2006 CRHTS, this study analyzed *home-origin trips* through four mode-specific models [= (weekday + weekend) * (trip frequency + travel time)]. The data were also used to evaluate *mode choice-related sociodemographics* with the following five indicators: female (yes/no), year of birth, household size, number of children, and number of automobiles.[4] [Compared to the total number of automobiles, as a standardized measure, the number of automobiles per driving license in a household can better account for car competition in the household. This study did not consider this particular variable, however, because the license variable had a considerable number of nonresponses: 478 cases (24.5%) out of a total of 1960. Income and job type variables were not analyzed for the same reason.]

This study measured *home-neighborhood land use* with six variables: (1) population density 1 (daytime) [daytime population = de jure (nighttime) population ± variations by commuters], population density 2 (de jure), bus stop density in the 0.5-mile skyline buffered area of the neighborhood, metro station density within the 0.5-mile buffer, street intersection density within the buffer, and land use entropy as evaluated in the buffered area: (−1) * [(s_1 / S) * ln(s_1 / S) + (s_2 / S) * ln(s_2 / S) + (s_3 / S) * ln(s_3 / S) + (s_4 / S) * ln(s_4 / S)] / ln(4), where s_x = the area of land use x (four in total: residential, business, commercial, and recreational) and S = the entire area of the four land uses.

Land use variables were all calculated using public GIS/GPS data (particularly, bus stop locations were identified using GPS coordinate data). Population densities were calculated with numerical population data from the Ministry of the Interior. To identify bus stop locations, this study downloaded GPS coordinate data from Bus Management System and to count metro stations, it obtained GIS polygon data from the New Address System. Street intersection points were created by processing street polyline data from the Highway Management System. Lastly, to identify neighborhood land uses, this study used GIS polygon data maintained by the Seoul Institute.

4 Results and analysis

4.1 Descriptive statistics and t-tests

Table 2 shows the descriptive statistics of the final sample. A larger amount of travel occurred on weekends than on weekdays regardless of the mode used and of the travel measure, be it trip frequency or travel time. This result is in agreement with previously identified travel patterns in Seoul [7]. The relative shares of the three modes were consistent between the weekday and weekend models in any case of travel measure: Public transit was the most frequently used, followed by the automobile and then by nonmotorized modes. Meanwhile, compared to the share of automobile travel, that of nonmotorized travel was a little larger when considering travel time rather than trip frequency; this variation may have been caused by different speeds of the two modes. Sociodemographics are representative of the overall individual and household characteristics of Seoul residents, except that individuals who live in a household with fewer children were slightly oversampled.

Table 3 shows the results of a total of six paired t-tests according to the three modes and two measures of travel. Differences between the two sample means, which were from the weekend and weekend samples, respectively, were significant in all cases. Based on these consistent weekday–

---

[3] The CRTHS selected 5331 block groups among a total of 13,832 in Seoul and from these sampled block groups, 102,000 households were recruited for the weekday survey (out of a total of 3,309,890 in Seoul) and 5102 for the weekend survey. For further details of the survey process, see Gim [39].

[4] As reviewed by Van Acker and Witlox [25], previous studies regarded automobile ownership either as a sociodemographic determinant of travel behavior—as with this study—or as a travel behavior outcome that is caused by land use and sociodemographic characteristics. Accordingly, they modeled automobile ownership as an intermediary as follows: land use and sociodemographics — > automobiles — > travel patterns. The model was found to account for larger variations in travel patterns and was used in their later studies [25, 46] and elsewhere [36, 47]. However, this study put automobile ownership as a sociodemographic indicator in order to be consistent with earlier and very recent Korean studies [48–52]. Further study is needed to test the significance of automobile ownership as an intermediary in Korean and other Asian settings. Such a study would be expected to find a larger effect of land use than this particular study because, as postulated by Van Acker and Witlox [25], compact developments lessen automobile travel not only directly, but also indirectly by discouraging automobile ownership. In support of this expectation, Næss [53] also observed such a larger land use effect by assuming that compact land use reduces automobile ownership.

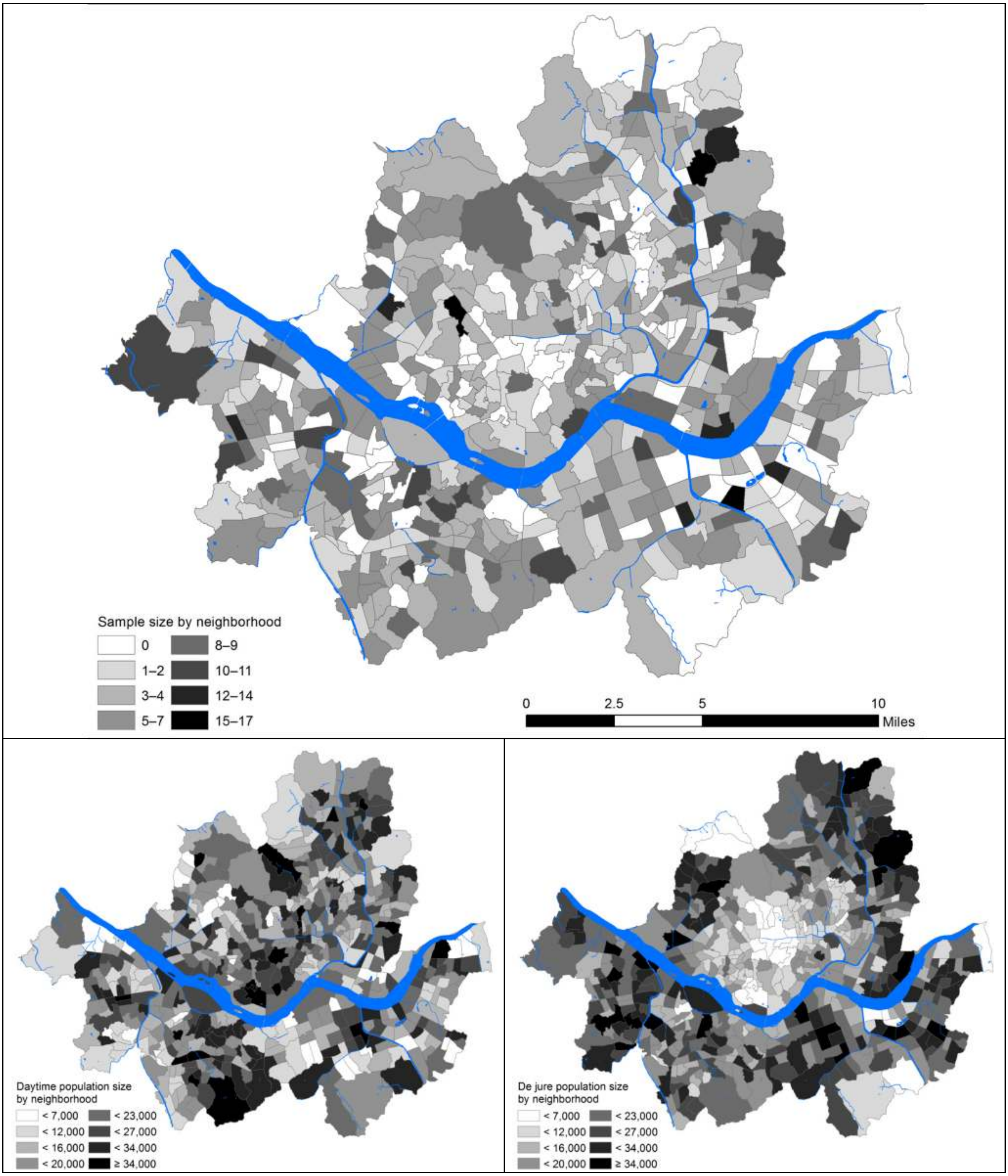


Fig. 1 Sample and population distributions. Note: For inferential statistics, the data should have good variations in research variables, but it is not mandatory to build a sample that matches the characteristics of the population (the sample representativeness is a major concern for descriptive statistics) [45]

weekend differences, this study employed SEM in order to establish the unseen relationships of sociodemographic and land use variables toward travel behavior on weekends versus weekdays.

Table 2 Descriptive statistics ($n = 1960$)

Factors	Variable descriptions (variable names)		Mean	S.D.	Min	Max
Travel behavior	Automobile weekday trip frequency (df_autom)		0.676	1.189	0	9
	Nonmotorized weekday trip frequency (df_non)		0.669	1.110	0	7
	Transit weekday trip frequency (df_transit)		0.938	1.680	0	20
	Automobile weekday travel minutes (dt_autom)		27.199	58.464	0	545
	Nonmotorized weekday travel minutes (dt_non)		13.035	27.485	0	440
	Transit weekday travel minutes (dt_transit)		30.819	58.149	0	680
	Automobile weekend trip frequency (ef_autom)		1.351	1.826	0	10
	Nonmotorized weekend trip frequency (ef_non)		1.059	1.627	0	12
	Transit weekend trip frequency (ef_transit)		1.911	2.176	0	14
	Automobile weekend travel minutes (et_autom)		78.509	139.332	0	1230
	Nonmotorized weekend travel minutes (et_non)		34.432	74.057	0	815
	Transit weekend travel minutes (et_transit)		88.511	121.700	0	855
Land Use	Bus stop density (avl_bus_d) [stops/mi^2]		129.899	57.800	6.147	272.728
	Metro station density (avl_met_d) [stations/mi^2]		1.369	0.879	0	4.892
	Street intersection density (cnn_d) [intersections/mi^2]		891.677	516.995	22.767	2361.104
	Land use entropy (ent) [Shannon entropy: 0–1]		0.584	0.157	0.184	0.981
	Daytime population density (pop1_d) [persons/mi^2]		67,992.582	52,014.381	97.261	411,117.750
	De jure population density (pop2_d) [persons/mi^2]		68,945.406	33,138.902	16.955	197,880.479
Socio-demo-graphics	Household automobiles (h_autom1)		0.834	0.568	0	4
	Household children (h_child)		0.099	0.347	0	2
	Household size (h_size)		3.799	0.993	1	7
	Birth year (m_birth)		1969.033	16.170	1926	2000
		Categories	f	%		
	Gender (m_gender)	Male (= 0)	883	45.1		
		Female (= 1)	1077	54.9		

4.2 Goodness-of-fit

Initial models were developed by specifying land use and sociodemographics as exogenous factors and travel behavior as an endogenous factor. When using SEM, initial models are required to allow for a correlation path between exogenous factors (i.e., sociodemographics ↔ land use or in Table 5, "LS < −-> LU").

First, this study removed all paths with p-values less than 0.1 from the initial models, and kept only those significant at the 90% confidence level. Then, the refined models were completed by adding paths that had an MI (modification index) of 10 or greater—paths were considered one by one in descending order of the MI—and if and only if they had theoretical grounds for inclusion. Regarding the grounds for the path inclusion, this study took a conservative approach. That is, regression paths were not taken into account as they alter the model structure. This study considered only correlation paths between the disturbances of indicator variables that are loaded onto the same factor (see Table 5). It is because in theory, these variables are assumed to be correlated, and their correlations are highly justifiable in comparison to those between indicators of different factors.

SEM requires one of the factor loadings to be fixed to one in each factor, as shown in Table 5. This study fixed different indicators in different models because in the process of parameter estimation, several models faced the issue of negative error variance, particularly in relation to disturbances for indicator variables (i.e., Heywood cases). The structures of the models are detailed elsewhere (https://drive.google.com/open?id=0B8PPoWtariY1VzJad3YwRzhjaG8). Negative variances often result from immoderate multicollinearity [54]; that is, they indicate that some indicators for the same factor "are sufficiently different, but nevertheless similar enough to measure the same concept" [55] (p. 99). A common solution to the negative variance issue is to assign a very small positive value (e.g., 0.005) to the variance, but according to the analysis of Chen et al. [23], this may distort parameter estimation. Thus, rather than assigning an arbitrary value, this study selected the very indicator with the negative variance to be fixed to one (instead of the originally fixed indicator) or added a correlation path between the disturbance and another; the validity of this correction has been confirmed [56, 57].

Inasmuch as different indicators were fixed, unstandardized coefficients—particularly, those of the fixed ones—

Table 3 Paired t-tests (n = 1960)

	Paired differences		t (d.f. = 1959)	p
	Mean	S.D.		
Automobile trip frequencies: weekday (df_autom) - weekend (ef_autom)	−0.674	1.712	−17.441	0.000
Nonmotorized trip frequencies: weekday (df_non) - weekend (ef_non)	−0.389	1.704	−10.116	0.000
Transit trip frequencies: weekday (df_transit) - weekend (ef_transit)	−0.973	2.589	−16.639	0.000
Automobile travel minutes: weekday (dt_autom) - weekend (et_autom)	−51.310	135.666	−16.744	0.000
Nonmotorized travel minutes: weekday (dt_non) - weekend (et_non)	−21.397	73.937	−12.812	0.000
Transit travel minutes: weekday (dt_transit) - weekend (et_transit)	−57.692	128.530	−19.872	0.000

cannot be consistently compared, but standardized coefficients are still comparable in the unit of the standard deviation; the standardized coefficient indicates the variation in an indicator (in the case of the factor-to-factor relationship, an outcome factor) in its standard deviation unit for a standard deviation change in its factor (or a predicting factor) [39].

Notably, as discussed in the introduction section, the sociodemographic factor was reflectively (not formatively) measured. This allows the meaning of the factor (i.e., mode choice-related sociodemographics) to remain constant, even though several indicators were insignificant and thus removed. Nonetheless, for configural invariance, it is safer to evaluate the factor based on the indicators that are consistently significant in all models [39, 58]: These indicators were the number of children and the household size. In this sense, a high value of the factor indicates people with more children and a bigger household.

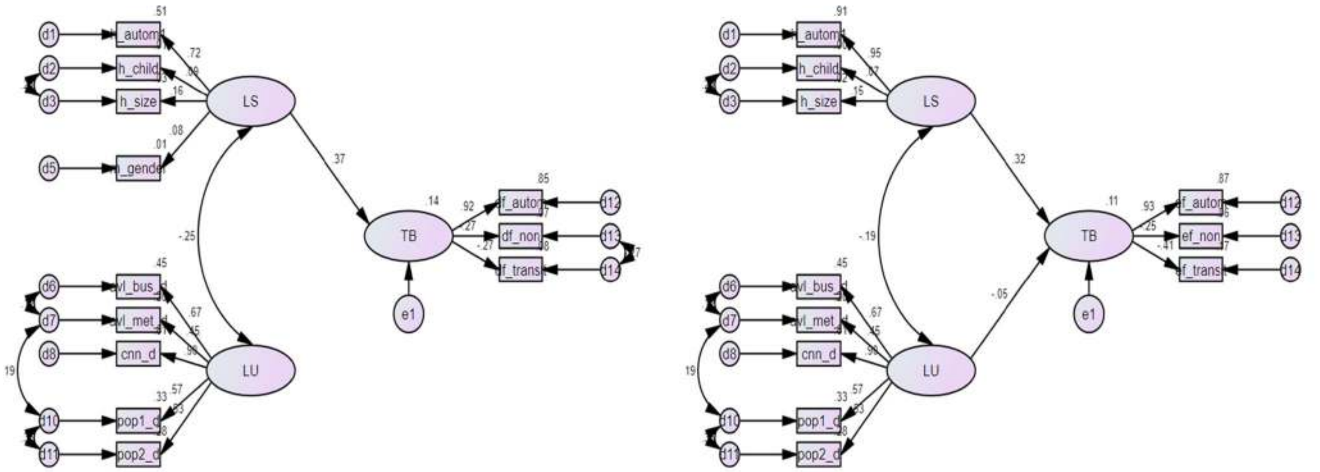
For the final models in Fig. 2, model files (.amw) as well as data (.sav) and output files (.AmosOutput) are available online at https://drive.google.com/open?id=0B8PPoWtariY1VzJad3YwRzhjaG8.

As shown in Table 4, all model fit indices demonstrate that all of the refined models are acceptable except χ^2. This statistic tends to erroneously reject a model if the sample size is 200 or more (in this study, sample size = 1960). Due to this limitation, two alternatives have been recommended: relative χ^2, and Hoelter's CN (critical number). Also called normed or normal χ^2, relative χ^2 is model χ^2 divided by the degree of freedom. The CN refers to the sample size above which the respective model is rejected; as stated above, the reference value is set to 200. When these two alternative indices were employed, all four models were deemed acceptable.

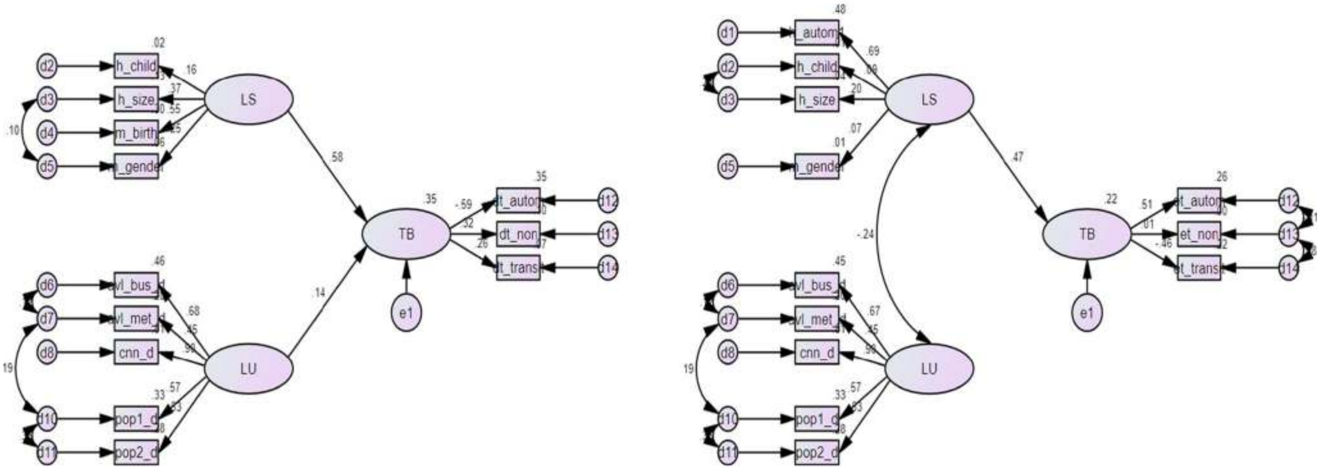
Also called covariance structure analysis, SEM is typically concerned with the covariances of the variables and factors: covariance fit or model fit. As a supplement, it may also consider variance fit, which is the same as R^2 of regression analysis. In Table 5, the SMC (squared multiple correlation) of travel behavior, which is a function of sociodemographics and land use (or only sociodemographics), shows that for both weekdays and weekends, the SEM models better account for variations in total travel time than for those in trip frequency. This finding—the higher explained variance in composite travel measures (e.g., total travel distance/time) than in trip frequency—supports Ewing and Cervero's argument [12], which was based on meta-analysis. While explained variances cannot be comparatively evaluated for weekend travel due to a lack of research on this topic, the weekday frequency model produced the SMC of 0.14, similar to previous studies, and the weekday time model (SMC = 0.36) outperformed most of them [57, 59]. (Statistically, the lower explained variance in trip frequency could be simply because it is a count outcome, which could be better modeled by a Poisson family model or an ordered logit/probit model. SEM, particularly maximum likelihood SEM, assumes the outcome to be continuous, and so it works better for composite travel measures such as travel time.)

4.3 Measurement model

The measurement model of SEM discloses the relationships between a factor and its indicator variables. First, the weekday and weekend models found differing results in terms of the relative magnitudes of travel variables (the differences were consistent regardless of the travel measure): automobile travel > nonmotorized travel ≳ transit travel in the two weekday models; automobile travel > transit travel > nonmotorized travel in the two weekend models. That is, automobile travel turned out to be the most sensitive to variations in the sociodemographic and land use factors, which implies that travel by automobile is a luxury—not necessity—good in South Korea as with other Asian countries. Regarding two other modes of travel, transit travel and nonmotorized travel



[Weekday trip frequency] [Weekend trip frequency]



[Weekday travel time] [Weekend travel time]

Fig. 2 Final SEM models. Note: Each of the three factors (in ovals) refers to sociodemographics (LS), land use (LU), and travel behavior (TB). All path coefficients (above paths) and SMCs (on the right shoulders of objects that are headed by regression paths) are shown in Table 4

did not differ considerably in terms of their sensitivity levels on weekdays, but on weekends, transit travel was more sensitive. This difference may be simply due to the fact that a good deal of weekend travel is long-distance travel [7], which is often be better served by public transit than by nonmotorized modes.

Regarding the effect that land use in Seoul has on travel behavior by *travel mode*, the weekday time model and the weekend frequency model—the only two models where land use was significant—showed that the direction (+/−) of the coefficient of each travel variable is consistent: automobile travel (−), transit travel (+), and nonmotorized travel (+). This indicates that, as expected, both transit travel and nonmotorized travel are substitute goods of automobile travel. This partially supports an argument of Aditjandra et al. [36]: Preference for transit travel and walk travel reduces automobile use. (This study is unable to determine the relationship between transit travel and nonmotorized travel; it is a relevant topic for further study [47].)

Among sociodemographic variables, this study found that the number of automobiles and household size are two major sociodemographic indicators. That is, the more automobiles and members their households had, the more likely people were to travel by automobile rather than by its alternatives. Notably, except for the weekday time model, all others found that automobile ownership is the single most important variable. Its magnitude overwhelmed that of the second strongest variable, household size, by 3.5–6.3 times. This result is in line with findings of previous studies [33, 60] and indicates that the findings can be extended to weekend travel without regard to travel measure. In relation to weekday travel time, however, automobile ownership was not even significant. Instead, age was the driver of transportation choice, that is,

Table 4 Covariance (model) fit

Indices	χ^2 Stat.	d.f.	p	Relative χ^2	Hoelter's CN ($\alpha = 0.05$)	Hoelter's CN ($\alpha = 0.01$)	SRMR
Cutoffs			Insig.	< 5	> 200	> 200	< 0.08
Weekday trip frequency	175.837	48	0.000	3.663	727	821	0.034
Weekday travel time	227.893	49	0.000	4.651	571	645	0.036
Weekend trip frequency	130.039	38	0.000	3.422	805	922	0.032
Weekend travel time	119.293	47	0.000	2.538	1052	1190	0.030
Indices	GFI	AGFI	CFI	RMSEA			
				Stat.	Lo 90	Hi 90	pclose
Cutoffs	> 0.9	> 0.9	> 0.9	< 0.08			Insig.
Weekday trip frequency	0.985	0.975	0.966	0.037	0.031	0.043	1.000
Weekday travel time	0.980	0.969	0.948	0.043	0.038	0.049	0.975
Weekend trip frequency	0.988	0.979	0.976	0.035	0.029	0.042	1.000
Weekend travel time	0.990	0.983	0.979	0.028	0.022	0.034	1.000

young people were more likely to use transit and nonmotorized travel modes instead of the automobile: birth year (standardized coefficient = 0.55) > household size (0.37). Considering that age had nothing to do with trip frequency on weekdays (according to the weekday trip frequency model), one might suspect that this result was led by age differences in choosing the preferred mode of transportation.

In relation to land use variables, their relative magnitudes were consistent in all SEM models: in descending order, street intersection density > bus stop density > daytime population density > de jure population density > metro station density (land use entropy was not significant in any of the models). Firstly, the finding that land use in Seoul is best stood for by street intersection density supports the arguments of previous studies [33, 61]; at the same time, inasmuch as the travel behavior factor hinges mostly on automobile use (df_autom in Table 5), the finding suggests that street intersection density is mainly related to automobile travel. It further implies that regardless of whether travel is measured by trip frequency or travel time, the argument applies to weekend travel as well as weekday travel. In fact, the few studies that analyzed the land use–travel relationship both on weekdays and weekends reported that street intersection density was consistently significant (however, they did not analyze the magnitude) [31, 32].

Secondly, this study assessed transit availability with metro and bus facility densities and consistently found that the latter better represents land use in Seoul. This finding can be attributed to the fact that buses are more readily available in most areas of Seoul. As in Table 2, people can, on average, access 130 bus stops and 1 metro station per square mile. Thirdly, by measuring population density in daytime and nighttime, this study found that daytime density is more representative of land use with regards to travel behavior. This is intuitively acceptable since a great majority of trips are embarked on in the daytime.

Lastly, the result that land use entropy was insignificant in all of the four models can be explained in two ways in relation to (1) the low accuracy of the land use balance measure and (2) the unique settings of the study area. In fact, several studies that found an insignificant/weak effect of land use entropy argued that this quantitative measure is inherently inaccurate because it cannot present on its 0–1 scale which land uses are more or less [62]. Moreover, it is not concerned with land use quality/aesthetics [63] (e.g., large shopping malls and small local stores are treated equally), land use structure in each neighborhood (in terms of the size of a land use patch and its shape, location, and continuity) [59], and diversity within one land use type (e.g., in commercial land use, differences between car dealerships and daily grocery stores are ignored) [64]. The insignificance can also be attributed in part to the fact that the entropy is related mainly to short (nonmotorized) travel rather than distant travel [33].

Meanwhile, Written et al. [32] similarly found that their land use mix measure is insignificant regardless of whether weekday or weekend travel is evaluated. Thus, if the insignificance of land use entropy is accepted as is, this result supports the notion that the entropy is not related to other land use variables in defining compact development. In general, a land use variable is believed to be correlated with others through spatial multicollinearity [21, 65, 66], but the entropy is not necessarily so. Many U.S. communities that are densely populated often lack workplaces, stores, and leisure facilities [67];

Table 5 Path coefficients

			Weekday trip frequency				Weekday travel time				Weekend trip frequency				Weekend travel time			
			Unstd. coef.*	Std. coef.	p	SMC	Unstd. coef.*	Std. coef.	p	SMC	Unstd. coef.*	Std. coef.	p	SMC	Unstd. coef.*	Std. coef.	p	SMC
Regression paths																		
df_autom	<---	TB	1 (fixed)	0.923		0.852	−2.256	−0.589	0.000	0.347	1 (fixed)	0.933		0.871	170.190	0.511	0.000	0.262
df_non	<---	TB	−0.275	−0.272	0.000	0.074	0.574	0.319	0.000	0.102	−0.236	−0.247	0.000	0.061	1 (fixed)	0.006		0.004
df_transit	<---	TB	−0.419	−0.274	0.000	0.075	1 (fixed)	0.261		0.068	−0.526	−0.412	0.000	0.170	−134.627	−0.464	0.000	0.215
h_autom1	<---	LS	1 (fixed)	0.715		0.512	(Removed)				1 (fixed)	0.952		0.906	2.003	0.693	0.000	0.480
h_child	<---	LS	0.080	0.094	0.002	0.009	0.006	0.157	0.000	0.025	0.042	0.066	0.006	0.004	0.160	0.090	0.004	0.008
h_size	<---	LS	0.390	0.159	0.000	0.025	0.041	0.366	0.000	0.134	0.283	0.154	0.000	0.024	1 (fixed)	0.198		0.039
m_birth	<---	LS	(Removed)				1 (fixed)	0.549		0.301	(Removed)				(Removed)			
m_gender	<---	LS	0.104	0.085	0.006	0.007	−0.014	−0.249	0.000	0.062	(Removed)				0.185	0.073	0.028	0.005
avl_bus_d	<---	LU	0.001	0.672	0.000	0.452	1 (fixed)	0.676		0.457	0.001	0.671	0.000	0.451	1 (fixed)	0.672		0.452
avl_met_d	<---	LU	0.000	0.449	0.000	0.202	0.010	0.450	0.000	0.202	0.000	0.448	0.000	0.201	0.010	0.449	0.000	0.202
cnn_d	<---	LU	0.016	0.902	0.000	0.813	11.884	0.898	0.000	0.807	0.016	0.903	0.000	0.815	11.999	0.902	0.000	0.813
ent	<---	LU	(Removed)				(Removed)				(Removed)				(Removed)			
pop1_d	<---	LU	1 (fixed)	0.570		0.325	758.191	0.570	0.000	0.325	1 (fixed)	0.570		0.325	762.615	0.570	0.000	0.325
pop2_d	<---	LU	0.587	0.525	0.000	0.276	446.045	0.526	0.000	0.277	0.588	0.525	0.000	0.276	447.913	0.525	0.000	0.276
TB	<---	LS	1 (fixed)	0.369		0.136	1 (fixed)	0.578		0.353	1 (fixed)	0.317		0.109	1 (fixed)	0.469		0.220
TB	<---	LU	(Removed)				0.054	0.139	0.000		0.000	−0.052	0.036		(Removed)			
Correlation paths																		
LS	<-->	LU	−2965.403	−0.247	0.000		(Removed)				−3031.314	−0.190	0.000		−1.860	−0.244	0.000	
d3	<-->	d2†	0.071	0.210	0.000		(Not added)				0.073	0.214	0.000		0.070	0.208	0.000	
d5	<-->	d3†	(Not added)				0.045	0.100	0.000		(Not added)				(Not added)			
d7	<-->	d6†	4.158	0.124	0.000		4.060	0.121	0.000		4.186	0.124	0.000		4.155	0.124	0.000	
d10	<-->	d7†	6235.451	0.186	0.000		6236.147	0.186	0.000		6244.384	0.186	0.000		6233.849	0.186	0.000	
d11	<-->	d10†	437,714,930.999	0.364	0.000		436,934,968.982	0.364	0.000		437,897,835.256	0.364	0.000		437,636,771.900	0.364	0.000	
d13	<-->	d12†	(Not added)				(Not added)				(Not added)				−944.949	−0.107	0.000	
d14	<-->	d13†	−0.469	−0.272	0.000		(Not added)				(Not added)				2256.126	0.284	0.000	

*SEM requires one factor loading per factor to be fixed to one for model identification purposes [39], and relative to their standardized counterparts, unstandardized coefficients do not carry meaningful information. However, presenting the unstandardized coefficients—particularly, showing which coefficient is fixed—is important by itself for the reproducibility of analytical findings [33]

† Added to the initial model based on the modification index

similarly, quite a few neighborhoods in Seoul have a high level of functional specialization (i.e., residential areas and office areas are geographically separated) [68].

4.4 Structural model

Different from the measurement model of SEM, the structural model tests the relationship between factors (between ovals in Fig. 2).

The sociodemographic effect was consistent across weekday and weekend travel: It had a stronger effect on travel time than trip frequency. That is, sociodemographics are more likely to change the destinations of trips than the frequency. The sociodemographic factor was best represented by automobile ownership in all models, except for the weekday travel time model where the variable was not even significant. Thus, owning one more automobile would result in the following changes: It *strongly* increases total travel time on weekends (e.g., it makes available more distant venues for low-cost/high-quality leisure activities) and *less strongly* increases weekday and weekend trip frequencies, whereas it has *no* meaningful effect on the choice of weekday trip destinations (e.g., there is usually no reason to travel to more distant offices/schools).

While the sociodemographic effect on travel behavior was consistent in the weekday and weekend models, the land use effect was entirely different. On weekdays, the land use effect was significant on travel time, but not on trip frequency; this confirms the findings of previous studies [12] and presumably results from the fact that weekday trips are mostly mandatory commute or work-related trips [in the weekday travel dataset, commute trips = 1586 (38.2%), work-related trips = 2166 (52.1%), shopping trips = 170 (4.1%), and leisure trips = 235 (5.7%)]. However, their finding may not be extended to weekend travel. On weekends, the land use effect on travel time was not even significant. Instead, the effect was significant on weekend trip frequency. [This echoes the findings of a previous study on travel time [4], where weekday travel time was affected by densities (household and commercial district) and rail station proximity, whereas weekend travel time had no relationship with land use variables.]

The differing results between weekday and weekend travel—the land use effect is significant on weekend trip frequency, but not on its weekday counterpart—can be explained by the *flexibility* of trip frequency [16]. For weekday travel, most of which has mandatory/compulsory purposes (e.g., commute and work-related travel) [69], people cannot choose to modify the number of trips itself in line with land use variations. By contrast, on weekends, when people mostly travel for nonmandatory/discretionary purposes (e.g., social and leisure) [6], it is relatively easy to change trip frequency [16].

Particularly on weekdays, land use in Seoul does not change trip frequencies (the path of "TB < −– LU" was removed from the weekday trip frequency model because it was insignificant). Also, because people in compact neighborhoods tend to use modes of travel that are slower than the automobile—and the alternatives are used to travel to the same destinations (e.g., office and school)—the total travel time somewhat increases (standardized coefficient of the path of "TB < −– LU" in the weekday travel time model = 0.139). However, this total time increase is not expected to cause traffic congestion because automobile travel time is negatively loaded onto the travel behavior factor (standardized coefficient of the path of "df_autom <−– TB" in the weekday travel time model = −0.589), that is, because automobile travel time is actually reduced.

Regarding weekend travel, the land use effect was significant on its trip frequencies (standardized coefficient of the path of "TB < −– LU" in the weekend trip frequency model = −0.052). Among the three modes of travel, land use in Seoul was negatively associated with automobile trips [in the weekend trip frequency model, the standardized coefficient of "df_autom <−– TB < −– LU" = 0.933 * (−0.052) = (−0.049)] and to a lesser degree, positively with those trips that are made by its alternatives [standardized coefficient(df_non < −– TB < −– LU) = (−0.247) * (−0.052) = 0.013 and standardized coefficient(df_transit <−– TB < −– LU) = (−0.412) * (−0.052) = 0.021]. This weekend trip frequency model supports Lin and Yu's finding [31]: As a single consistently significant variable, street intersection density negatively affected the likelihood of a weekend (unorganized) trip, but it positively affected the choices of walking, biking, and public transit. Notably, this study found that fewer automobile trips and more transit and nonmotorized trips did not result in changes in total travel time. A possible reason is that in relation to travel time, a *larger* reduction of *faster* automobile trips was canceled out by a *smaller* addition of *slower* nonmotorized trips.

All in all, by comparing the effects that land use in Seoul has on weekday and weekend travel, this study found that compact development results in extended total travel time accompanied by the constant number of trips on weekdays and *fewer trips* on weekends; in particular, there are fewer weekend trips *by automobile* in accordance with the negative correlations between automobile trips and transit and nonmotorized trips. Furthermore, this study supports the argument of previous studies that with focus on weekday trip frequency, empirical studies may find a relatively weak effect of land use compared to the sociodemographic effect; this, unfortunately, would discourage transportation planners from considering land use interventions that may have other benefits. Particularly regarding weekend travel, the findings suggest that empirical studies would reach a discouraging conclusion if they highlight the land use effect on travel time only. However, such a suggestion should be considered with caution since this study relied on data from a trip-based household travel survey with a predetermined spatial unit [70]. For land use policy implications at the strategic level, an appropriate regional-scale analysis appears to be more desirable; for example, see Aditjandra [71].

5 Conclusions

Only a few studies examined the land use effect on weekend travel in comparison with the effect on weekday travel, and none of those analyzed the same sample. As such, it is not clear whether differences in analytical results were led by variations in the days of travel or in the samples. This study fills this gap by using the same sample for its SEM models. The models were constructed for weekday and weekend travel, each of which was again separated to measure both trip frequency and travel time.

Among variables that reflect the factor of mode choice-related sociodemographics, the two weekend travel models (trip frequency and travel time models) found that automobile ownership greatly increases automobile travel, suggesting that the findings of weekday travel studies are applicable to weekend travel. Overall, the sociodemographic factor exerted a stronger effect on travel time than on trip frequency for both weekday and weekend travel. This implies that if sociodemographics become favorable to automobile travel, people are more likely to drive to more distant destinations—which leads to longer overall trip time—rather than visiting the same destinations more frequently.

In all models, indicator variables that reflect land use were found to be consistent in their relative magnitudes. Street intersection density was the most important, which supports the weekday findings of previous studies and extends it to weekend travel. Secondly, this study separated population density into daytime and nighttime densities and transit availability into bus and metro facility densities. It then found that the relative importance is determined by how well the land use measure represents temporal and spatial ranges in which trips take place. That is, one of the reasons daytime population density and bus stop density were more important is that daytime population reflects traffic peak hours, when trips are concentrated, and bus service covers both intra- and inter-neighborhood destinations [72].

Among the three modes of travel, land use in Seoul discouraged automobile travel, specifically automobile travel time on weekdays and automobile trip frequency on weekends. Instead, it facilitated transit and nonmotorized travel. In terms of the overall land use effect on weekday travel, it was significant on travel time rather than on trip frequency; this echoes the findings of the previous literature. In the weekend travel models, however, the opposite result was found: The land use effect was not significant on travel time, but on trip frequency. On weekdays, when most trips are compulsory (e.g., commuting and business), people in compact neighborhoods cannot easily change trip frequency. Instead, they are likely to shift to alternatives to the automobile, implying increases in travel time. On weekends, however, they may reduce the number of trips, most of which have discretionary purposes (e.g., social and leisure activities). Specifically, they would embark on a reduced number of trips by automobile, but the reduction is unlikely to be fully compensated for by the addition of transit and nonmotorized trips.

The findings of this research suggest that land use policies should be analyzed considering different travel measures holistically, as recommended by van Acker and Witlox [25]. For example, a reduction in travel time can be achieved either by increasing the share of automobile travel (which is faster) or by reducing the overall trip length, which subsequently reduces the overall trip time. Thus, as policy implications for planning practitioners, first, it is advised to consider that compact city strategies have different effects on weekdays and weekends. Specifically, the strategies would lead to a reduced number of trips on weekends, but on weekdays, they may result in the extended travel time. Notably, the extension is not attributed to traffic congestion but to the use of automobile alternatives that have inferior mechanical characteristics (e.g., slower speed, frequent stops, and fixed—often not the shortest—routes) [73–75]. Planners then may intend to improve alternative modes of travel in order to make them more competitive in terms of speed, timeliness, and convenience [76]. Regarding land use variables, in order to reduce automobile trips on weekends, planners can first aim to increase street intersection density, as this feature is the best reflection of the compact city concept (this finding has also been reported in a study conducted in Boston and Hong Kong [61]). The intersection density increase may be done by revising subdivision and street design regulations to reduce the number and length of dead-end streets and the size/length of blocks [77]. Secondly, bus stop density turned out to be more important than metro station density. Thus, it is recommended to facilitate bus services for the purpose of increasing transit ridership and reducing automobile travel. An attractive option is to improve the level of service of connector buses to metro stations, since 89.2% of transit riders in Seoul transfer between bus and metro [8]. Lastly, while compact city strategies are often summarized with density measures [28, 78], daytime/activity density (e.g., employment density) may be a better reference for zoning and building codes than nighttime/permanent density (e.g., residential density) in revising minimum and maximum building heights and densities. Other measures for higher activity density include the introduction of density bonuses—in return for the ability to build lucrative higher density developments, developers are required to provide neighborhood amenities such as parks, plazas, retail space, and public places—and revisions to building requirements on floor area ratio, minimum lot size and setback, and expansion by room/floor additions.

This study had several limitations. First, due to data limitations, people's individual characteristics were evaluated only with sociodemographic variables, though previous studies [18, 21] have repeatedly showed attitudinal variables to be important. In relation to residential self-selection, if people choose to live in a neighborhood according to their attitudes toward its land use, then a travel behavior model would lead to an overestimation of the effects of land use variables. If the confounding effects of the attitudinal variables are not controlled for in the model, the land use–travel relationship becomes spurious. The magnitude of the self-selection effect has been discussed in several reviews of the literature [9, 10, 79, 80].

Second, to explain its empirical results, this study relied on the concept of *flexibility* or as developed by Goulias and Kitamura [16], the typology of *compulsory and discretionary travel* (or mandatory and nonmandatory travel). Specifically, weekday travel, which is mostly compulsory (e.g., commute), has less flexibility in changing the number of trips according to land use variations. In contrast, weekend travel is often discretionary (e.g., leisure). Accordingly, the frequency of weekend trips can be more flexibly modified. Thus, if data on travel purposes are fully available,[5] studies are recommended to compare purpose-specific models for both weekday and weekend travel to allow for more detailed analysis of the land use–travel relationship. Lastly, this study could not examine possibly important variables such as subjective/perceived land use characteristics [81]. Subjective land use variables have been reported to be significant travel determinants whose magnitude is similar to or larger than their objective counterparts [46, 64]. Thus, it is desirable to include both objective and subjective land use variables in analytical models.

Acknowledgements The paper benefited greatly from technical supports by graduate students in Seoul National University Integrated Planning Lab, particularly by Ryan Dash and Su Kim, and from constructive comments by the associate editor and the two anonymous reviewers.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is distributed under the terms of the Creative Commons Attribution 4.0 International License (http://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made.

References

1. Handy SL (2005) Smart growth and the transportation–land use connection: what does the research tell us? Int Reg Sci Rev 28(2): 146–167
2. Bhat CR, Gossen R (2004) A mixed multinomial logit model analysis of weekend recreational episode type choice. Transp Res B 38(9):767–787
3. Liu RR, Deng Y (2009) Developing statewide weekend travel-demand forecast and mode-choice models for New Jersey. In: Sloboda BW (ed) Transportation statistics. J. Ross Publishing, Fort Lauderdale, pp 231–248
4. Lee Y, Washington S, Frank LD (2009) Examination of relationships between urban form, household activities, and time allocation in the Atlanta metropolitan region. Transp Res A 43(4):360–373
5. Manaugh K, El-Geneidy A (2012) What makes travel 'local': defining and understanding local travel behaviour. J Transp Land Use 5(3):15–27
6. Rajamani J, Bhat CR, Handy S, Knaap G, Song Y (2003) Assessing the impact of urban form measures on nonwork trip mode choice after controlling for demographic and level-of-service effects. Transp Res Rec 1831:158–165
7. Ryu S (2014) Comparing weekday and weekend travel patterns of the Korean capital region residents. Gyeonggi Research Institute, Suwon
8. Seoul Statistics (2016) Statistics on Seoul citizens' public transportation use. Seoul Metropolitan Government. http://stat.seoul.go.kr/jsp3/webzine.view.jsp?wj_id=109&link=5&sublink=2016. Accessed 8 Oct 2017
9. Gim T-HT (2011) A meta-analysis of the relationship between density and travel behavior. Transportation 39(3):491–519
10. Cao X, Mokhtarian PL, Handy SL (2009) Examining the impacts of residential self-selection on travel behaviour: a focus on empirical findings. Transp Rev 29(3):359–395
11. Badoe DA, Miller EJ (2000) Transportation–land-use interaction: empirical findings in North America, and their implications for modeling. Transp Res D 5(4):235–263
12. Ewing R, Cervero R (2001) Travel and the built environment: a synthesis. Transp Res Rec 1780:87–113
13. Gordon I (2008) Density and the built environment. Energy Policy 36(12):4652–4656
14. Melia S, Parkhurst G, Barton H (2011) The paradox of intensification. Transp Policy 18(1):46–52
15. Maat K, van Wee B, Stead D (2005) Land use and travel behaviour: expected effects from the perspective of utility theory and activity-based theories. Environ Plann B 32:33–46
16. Goulias KG, Kitamura R (1989) Recursive model system for trip generation and trip chaining. Transp Res Rec 1236:59–66
17. Meurs H, van Wee B (2004) Land use and mobility: a synthesis of findings and policy implications. Eur J Transp Infrastruct Res 3(2): 219–233
18. Mokhtarian PL, Cao X (2008) Examining the impacts of residential self-selection on travel behavior: a focus on methodologies. Transp Res B 42(3):204–228
19. Cao X, Mokhtarian PL, Handy SL (2007) Do changes in neighborhood characteristics lead to changes in travel behavior? A structural equations modeling approach. Transportation 34(5):535–556
20. Næss P (2005) Residential location affects travel behavior—but how and why? The case of Copenhagen metropolitan area. Prog Plan 63(2):167–257
21. T-HT G (2013) The relationships between land use measures and travel behavior: a meta-analytic approach. Transp Plan Technol 36(5):413–434
22. Gim T-HT (2017) Examining the effects of residential self-selection on internal and external validity: an interaction moderation analysis

---

[5] The data of the supplementary weekend survey had a considerable number of missing values for the travel purpose variable. Indeed, unlike its predecessors, the 2006 CRHTS conducted the supplementary survey, but the questionnaire had a shorter list of questions that were in a less detailed format than that of the main weekday survey.

using structural equation modeling. Transp Lett. https://doi.org/10.1080/19427867.2017.1338544

23. Churchill GA (1979) A paradigm for developing better measures of marketing constructs. J Mark Res 16(1):64–73
24. Coltman T, Devinney TM, Midgley DF, Venaik S (2008) Formative versus reflective measurement models: two applications of formative measurement. J Bus Res 61(12):1250–1262
25. Van Acker V, Witlox F (2011) Commuting trips within tours: how is commuting related to land use? Transportation 38(3):465–486
26. Rutherford GS, Mccormack E, Wilkinson M (1997) Travel impacts of urban form: implications from an analysis of two Seattle area travel diaries. Proceedings of urban design, telecommuting and travel forecasting conference, Williamsburg, pp 95–166
27. Troped PJ, Wilson JS, Matthews CE, Cromley EK, Melly SJ (2010) The built environment and location-based physical activity. Am J Prev Med 38(4):429–438
28. Forsyth A, Oakes JM, Schmitz KH, Hearst M (2007) Does residential density increase walking and other physical activity? Urban Stud 44(4):679–697
29. Cervero R, Duncan M (2003) Walking, bicycling, and urban landscapes: evidence from the San Francisco bay area. Am J Public Health 93(9):1478–1483
30. Ogilvie D, Mitchell R, Mutrie N, Petticrew M, Platt S (2008) Personal and environmental correlates of active travel and physical activity in a deprived urban population. Int J Behav Nutr Phys Act 5(1):43
31. Lin J-J, Yu T-P (2011) Built environment effects on leisure travel for children: trip generation and travel mode. Transp Policy 18(1):246–258
32. Witten K, Blakely T, Bagheri N, Badland H, Ivory V, Pearce J, Mavoa S, Hinckson E, Schofield G (2012) Neighborhood built environment and transport and leisure physical activity: findings using objective exposure and outcome measures in New Zealand. Environ Health Perspect 120(7):971–977
33. T-HT G (2011) Influences on trip frequency according to travel purposes: a structural equation modeling approach in Seoul, South Korea. Environ Plann B 38(3):429–446
34. Bhat CR, Srinivasan S (2005) A multidimensional mixed ordered-response model for analyzing weekend activity participation. Transp Res B 39(3):255–278
35. Lanzendorf M (2002) Mobility styles and travel behavior: application of a lifestyle approach to leisure travel. Transp Res Rec 1807: 163–173
36. Aditjandra PT, Cao X, Mulley C (2012) Understanding neighbourhood design impact on travel behaviour: an application of structural equations model to a British metropolitan data. Transp Res A 46(1):22–32
37. Bagley MN, Mokhtarian PL (2002) The impact of residential neighborhood type on travel behavior: a structural equations modeling approach. Ann Reg Sci 36(2):279–297
38. Van Acker V, Witlox F, van Wee B (2007) The effects of the land use system on travel behavior: a structural equation modeling approach. Transp Plan Technol 30(4):331–353
39. Gim T-HT (2013) Utility-based approaches to understanding the effects of urban compactness on travel behavior: a case of Seoul, Korea. Dissertation, Georgia Institute of Technology
40. Jun M-J, Jeong J-E (2011) Analysis on spatial mismatch and excess commuting of the Seoul metropolitan area using cubic spline function and linear programming. Journal of Korea Planning Association 46(4):189–197
41. Lee K (2013) Impacts of neighborhood's land use and transit accessibility on residents' commuting trips: a case study of Seoul. Journal of the Korea Academia–Industrial Cooperation Society 14(9):4593–4601
42. Lee KH, Kim TH, Lee WM, Kim EJ (2014) A study on effects of neighborhood's environments on residents' walking trips using household travel diary survey data in Seoul. Seoul Studies 15(3): 95–109
43. Min B, Lee G, Kim S (2016) The effects of land-use characteristics on trip patterns by trip modes and purposes: focused on Seoul metropolitan administrative division. Journal of the Architectural Institute of Korea: Planning and Design 32(4):77–87
44. Shin S-Y (2004) The relationship between land use and automobile dependence: the case of Seoul. Seoul Studies 5(1):71–93
45. Ory DT (2007) Structural equation modeling of relative desired travel amounts. Dissertation, University of California, Davis
46. Van Acker V, Mokhtarian PL, Witlox F (2011) Going soft: on how subjective variables explain modal choices for leisure travel. Eur J Transp Infrastruct Res 11(2):115–146
47. Aditjandra PT, Cao X, Mulley C (2016) Exploring changes in public transport use and walking following residential relocation: a British case study. J Transp Land Use 9(3):77–95
48. Cho H, Lee S (2016) Analysis of neighborhood environmental characteristics affecting walking activity time: focused on the difference between subjectively measured- and objectively measured-neighborhood environment. J Korea Plan Assoc 51(4):105–122
49. Choi S-T, Choo S-H, Jang J-Y (2016) Identifying the characteristics of elderly pedestrian using the Tobit model. J Korea Inst Intell Transp Syst 15(1):16–27
50. Kim H-C, Ahn K-H, Kwon Y-S (2014) The effects of residential environmental factors on personal walking probability: focused on Seoul. Urban Des 15(3):5–18
51. Lee KH, Ko EJ (2014) Relationships between neighbourhood environments and residents' bicycle mode choice: a case study of Seoul. Int J Urban Sci 18(3):383–395
52. Lee KH, Won DH, Ko EJ (2015) The multiple impacts of the neighbourhood environment on the use of public bicycles by residents: an empirical study of Changwon in Korea. Int J Urban Sci 19(2):224–237
53. Næss P (2009) Residential self-selection and appropriate control variables in land use: travel studies. Transp Rev 29(3):293–324
54. Chen F, Bollen KA, Paxton P, Curran PJ, Kirby JB (2001) Improper solutions in structural equation models: causes, consequences, and strategies. Sociol Methods Res 29(4):468–508
55. Blunch NJ (2013) Introduction to structural equation modeling using IBM SPSS statistics and AMOS. Sage, London
56. Choo S (2005) Aggregate relationships between telecommunications and travel: structural equation modeling of time series data. Dissertation, University of California, Davis
57. Scheiner J, Holz-Rau C (2007) Travel mode choice: affected by objective or subjective determinants? Transportation 34(4):487–511
58. Byrne BM (2010) Structural equation modeling with AMOS: basic concepts, applications, and programming. Routledge, New York
59. Handy SL (1996) Understanding the link between urban form and nonwork travel behavior. J Plan Educ Res 15(3):183–198
60. Pucher J, Renne JL (2003) Socioeconomics of urban travel: evidence from the 2001 NHTS. Transp Q 57(3):49–78
61. Zhang M (2004) The role of land use in travel mode choice: evidence from Boston and Hong Kong. J Am Plan Assoc 70(3):344–360
62. Brown BB, Yamada I, Smith KR, Zick CD, Kowaleski-Jones L, Fan JX (2009) Mixed land use and walkability: variations in land use measures and relationships with BMI, overweight, and obesity. Health Place 15(4):1130–1141
63. Christian HE, Bull FC, Middleton NJ, Knuiman MW, Divitini ML, Hooper P, Amarasinghe A, Giles-Corti B (2011) How important is the land use mix measure in understanding walking behaviour? Results from the RESIDE study. Int J Behav Nutr Phys Act 8(1):55
64. T-HT G (2011) A comparison of the effects of objective and perceived land use on travel behavior. Growth Chang 42(4):571–600

65. Osman T, Divigalpitiya P, Arima T (2016) Driving factors of urban sprawl in Giza governorate of the greater Cairo metropolitan region using a logistic regression model. Int J Urban Sci 20(2):206–225
66. Lee S, Suzuki T (2016) A scenario approach to the evaluation of sustainable urban structure for reducing carbon dioxide emissions in Seoul. Int J Urban Sci 20(1):30–48
67. Nivola PS (1999) Laws of the landscape: how policies shape cities in Europe and America. Natural Resources Defense Council, New York
68. Choi E, Heo H, Sung H, Kim E (2010) A study on the estimation of sprawl index and its relationship with travel pattern in the capital region. Korea Spat Plan Rev 64:97–112
69. Lin D, Allan A, Cui J (2017) Sub-centres, socio-economic characteristics and commuting: a case study and its implications. Int J Urban Sci 21(2):147–171
70. Anda C, Erath A, Fourie PJ (2017) Transport modelling in the age of big data. Int J Urban Sci 21(supplement 1):19–42
71. Aditjandra PT (2013) The impact of urban development patterns on travel behaviour: lessons learned from a British metropolitan region using macro-analysis and micro-analysis in addressing the sustainability agenda. Res Transp Bus Manag 7(Supplement C):69–80
72. Thilakaratne RS, Wirasinghe SC (2016) Implementation of bus rapid transit (BRT) on an optimal segment of a long regular bus route. Int J Urban Sci 21(1):15–29
73. Cui J, Loo BPY, Lin D (2017) Travel behaviour and mobility needs of older adults in an ageing and car-dependent society. Int J Urban Sci 21(2):109–128
74. Loo BPY, du Verle F (2017) Transit-oriented development in future cities: towards a two-level sustainable mobility strategy. Int J Urban Sci 21(Supplement 1):54–67
75. Zhang X, Riedel T (2017) Urban traffic control: present and the future. Int J Urban Sci 21(Supplement 1):87–100
76. Oguchi T, Mitsuyasu A, Oshima D, Imagawa T (2017) An evaluation study on advanced public transport priority system using traffic simulation. Int J Urban Sci 21(Supplement 1):43–53
77. Song Y, Knaap G-J (2004) Measuring urban form: is Portland winning the war on sprawl? J Am Plan Assoc 70(2):210–225
78. Ramani TL, Zietsman J (2016) Sustainable transportation—alternative perspectives and enduring challenges. Int J Urban Sci 20(3): 318–333
79. Ewing R, Cervero R (2010) Travel and the built environment: a meta-analysis. J Am Plan Assoc 76(3):265–294
80. Mokhtarian PL, van Herick D (2016) Quantifying residential self-selection effects: a review of methods and findings from applications of propensity score and sample selection approaches. J Transp Land Use 9(1):9–28
81. Kim Y (2016) Impacts of the perception of physical environments and the actual physical environments on self-rated health. Int J Urban Sci 20(1):73–87