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Land-use patterns, location choice, and travel behavior: Evidence from São Paulo

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Abstract: Global South cities are vastly underrepresented in the literature that analyzes the relationships between location choice, land-use patterns and travel behavior. This paper aims to reduce that underrepresentation by bringing new evidence from a metropolitan region in the Global South. We estimate a Structural Equation Model to study the relationships between land-use patterns, location choice, car ownership and travel behavior, while controlling for self-selection, in the metropolitan region of São Paulo, Brazil. The model structure is adapted from previous applications to include variables related with specific aspects of the studied region, with the inclusion of informal work and people working two jobs, while simultaneously controlling for cohort effects associated with being a millennial. The results support the claim that land-use patterns influence travel behavior, even in a metropolitan area showing strong income-based spatial segregation levels. More specifically, commuting distance and car ownership act as important mediators in the relationships between the total amount of travel by mode and land-use patterns. In contrast to previous applications of this model framework, income plays a stronger role, an indication of relevant income-based residential sorting. Cohort effects are also visible, as millennials prefer to live in central, accessible, and mixed areas, own fewer cars, travel less by car, and use public transit and non-motorized modes more frequently.

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1 Introduction

The continuous growth in car use to meet commute and other urban travel demands has pushed transportation planners to find strategies for promoting more sustainable transportation modes and reducing externalities. Land-use policies aimed at reducing sprawl, increasing the density and diversity of urban areas, and providing adequate infrastructure supporting the use of public transportation and non-motorized modes, are some among the suite of policies aimed at curbing the use of cars and achieving more sustainable travel patterns. Since the early 1990s, an important amount of research work focusing on the study of the effectiveness of these policies, or more appropriately, the study of the mechanisms implied by them (the effects of land-use patterns on travel behavior) has been published,

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with several reviews and meta-analysis featured in the literature (e.g., Badoe & Miller, 2000; Cao et al., 2009; Ewing & Cervero, 2001, 2010; Handy, 1996; Stevens, 2017; Wang & Zhou, 2017).

The vast majority of the published research focuses on case studies from North America and Western Europe. Although efforts have been made to understand these interactions in Latin America and African cities (Acheampong, 2018; Basso et al., 2020; Guerra et al., 2018; Guzman et al., 2020; Zegras, 2004), the literature still lacks a more holistic approach to such contexts, which are clearly under-represented. This lack of research constitutes a significant gap, as Latin America faces urbanization processes that are distinct from those in European and North American cities (Gomez et al., 2015). Inequality in the location of jobs and public services resulting from disorganized urban growth led to high levels of spatial segregation boosted by car-oriented public policies (Cervero, 2013; Cervero et al., 2009). Inequality, poverty, and lack of opportunities increase levels of criminality across many of these cities, forcing individuals to consider public security when choosing to walk, ride a bike, or use public transportation (Guzman et al., 2017; Larranaga et al., 2018; Lucchesi et al., 2021; Tucker & Manaugh, 2018). Indeed, economically vulnerable populations may reveal different travel patterns from the mainstream, but mostly because they are more likely to be spatially segregated (Shanqi et al., 2021). Accordingly, studying the effect of land-use patterns on travel behavior in Latin American cities, while controlling for possible individual and household characteristics that could help to explain spatial segregation and residential sorting based on socioeconomic characteristics, is an important research endeavor.

Regarding socioeconomic aspects, factors such as age, income, and gender are essential characteristics to understanding location choice and travel behavior. Different age cohorts respond differently to built environment stimuli and are more attentive to their lifestyle impacts and wellbeing (Lucchesi et al., 2021a). Studies conducted in North America, Asia, and Europe have shown that young adults have different concerns and reveal different behavioral patterns. Research on this topic in the Latin American context is rather scarce. Millennials are more concerned about the environment (Hopkins, 2016) and more likely to use shared mobility systems (Circella et al., 2017; Lee & Circella, 2019). They also prefer living in denser areas (Melia et al., 2018), travel less (Klein & Smart, 2017), and have less cars (Klein & Smart, 2017). However, more recent research on this topic concludes that besides cohort effects, the lasting effects of the 2008 crisis (lower income, unemployment, precarious jobs and financial dependency from parents) are also responsible for millennials' behavior (Garikapati et al., 2016; Klein & Smart, 2017).

The above-mentioned gaps, related with both the limited amount of research that focuses on the influence of land-use patterns on travel behavior and the incorporation of cohort effects in relation to young adults in a Latin American context, are the reason for this work. To this end, we use a recent travel survey from the São Paulo Metropolitan Region (RMSP). Using São Paulo as a case setting means that one can introduce other aspects into the discussion, particularly the problems associated with urban inequalities and residential sorting. Finally, and to the best of our knowledge, this is the first study to specifically take millennials into account and represent that generation's behavioral changes in a Brazilian context.

We adapt a Path Analysis Model Framework, originally developed by de Abreu e Silva et al. (2006), which has been tested for several metropolitan areas in North America and Europe: Lisbon (de Abreu e Silva, Golob & Goulias, 2006; de Abreu e Silva, Martinez, & Goulias, 2012), Seattle (de Abreu e Silva & Goulias, 2009); Montreal (de Abreu e Silva, Morency, & Goulias, 2012), and the Southern California Association of Governments (SCAG – Los Angeles and surrounding counties) (de Abreu e Silva, Goulias, & Dalal, 2012). While these cities have their own specific particularities, they are all located in developed countries, and have high urban infrastructure standards and a lower level of social disparities. However, more importantly, the general model structure holds in all these case studies, and the global conclusions are in alignment, adding weight to the argument in favor of its robustness. Accordingly, it was deemed appropriate to test this model framework in a Latin America Megapolis context.

The remainder of this paper is organized as follows. First, the study settings and the general characteristics of the data used herein are presented, followed by the structure of the general model and its main assumptions. The next section features the model results and a discussion of the obtained results. Finally, in the conclusions, the policy implications and a brief comparison with the results obtained in the other settings using the same model framework are presented.

2 Case setting and model description

This research uses data from an Origin-Destination Survey conducted in the Metropolitan Region of São Paulo (RMSP) in 2017. The RMSP is the biggest metropolitan region in Latin America by population, with more than 21 million inhabitants and comprises 39 cities. Its spatial characteristics, distribution of infrastructures and public resources (Haddad & Nedović-Budić, 2006), as well as the socioeconomic characteristics of its population, show a clear dichotomy between the center and the periphery. The urban inequalities that exist in São Paulo also affect how citizens commute. Low-income families have a small range of places where they can afford to live. These financial constraints contribute to residential sorting, the most extreme examples of which are the multiple slums within the metropolitan region structure. For more affluent individuals, residential self-selection, which means that individuals will be able to settle in places allowing them to pursue their desired lifestyles (e.g., Cao et al. 2009) could still be a possibility. The RMSP has a total surface area of 1.029 thousand sq. ha and is divided into 517 traffic analysis zones (TAZs).

The survey sample size comprises 32 thousand households. Aside from household and individual socioeconomic characteristics, the survey collected all spatial-temporal characteristics of the trips made by all household members for the day before the survey date. As the model focuses on adult workers, we randomly selected one 18 year old or older worker (with either a formal or informal job) who declared having traveled on the travel diary date. Including all workers in the household would mean the need to control for intra-household interactions[1], an interesting and important research objective, but it would prevent the use of the adopted model structure and a comparison with the other settings in which the same framework was used. Accordingly, it was necessary to randomly select only one worker per household, while ensuring that the resulting sample was in line with the distribution of the working population of São Paulo.

This selection, after data cleaning, resulted in a database with 18,352 observations. The socioeconomic variables considered include age; gender; income; household size; the average age of the adults in the household; the number of employed people in the household; if the household has only one or two people (to account for non-linear effects in household size); if the respondent has an informal job (which would normally mean a low wage and low job security); if the respondent has two jobs (as a form of supplementing their income); and if the respondent is a millennial. The income variable used here is a classification criterion developed by Brazilian survey companies (http://www.abep.org/criterio-brasil) to classify households in different categories according to their purchasing power.

The land-use variables are built using three different data sources: (i) data from the census conducted in 2010; (ii) information available from Open Street Map (OSM); and (iii) open data sources from the municipalities belonging to the RMSP. Land-use variables are built both for the TAZ of the residence and the main job of each respondent. The land-use variables include density; the mix of jobs

[1] Intra-household interactions incorporate the effects that one member of the household could have on others, including group decision-making, distribution of household resources (e.g. car), tasks and activities (Ho & Mulley, 2015).

and inhabitants; distance to the CBD; an entropy indicator (Kockelman, 1997) measuring the distribution among residential and commercial (retail, restaurants, and amenities) land uses; accessibility ratios between public transit/car and non-motorized modes/car using the gravitational accessibility approach (de Abreu e Silva, 2014); the percentage of people located 400 meters around a bus stop or a heavy transit (rail) station; the percentages of people located 1,000 meters away from a freeway node (represented by a point centered on an intersection); and km of road per capita.

The accessibility ratio variables are estimated using the following general formula:

$$\frac{Acc_i^k}{Acc_i^{car}} = \frac{\sum_j e^{\beta \times T_{ij}^k} \times Op_j^k}{\sum_j e^{\beta \times T_{ij}^{car}} \times Op_j^{car}} \quad (1)$$

Where Acc_i is the accessibility indicator, k is either a public transit or non-motorized mode, β is the impedance parameter, T is the travel time, and Op are the travel opportunities, which are here taken as applying to the total number of residents and workers.

The variables using population were calculated considering the centroid of each census tract zone. When the centroid falls inside the buffer, the full population and workers of each census tract are considered as being inside of it. Figure 1 presents an example using the heavy public transit stations' locations, the 400 m buffer zones (brown circles) and the census tract centroids (pink points).

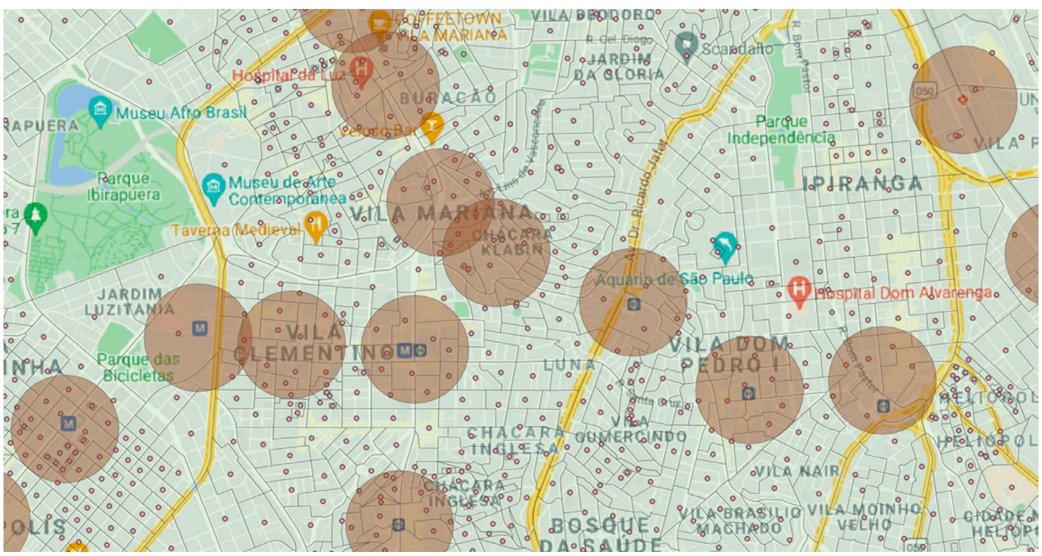

Figure 1. Heavy transit 400 m buffer zones and census tract centroids

Table 1 presents the home-based and work-based land use parameter's descriptive statistics and the socioeconomic variables included in the model. Figure 2 presents the model's general structure. The socioeconomic, land use and travel behavior variables are similar to those used in the first study using this framework (de Abreu e Silva, Golob & Goulias, 2006). To account for the specific characteristics of the Brazilian context (informal job and working two jobs) and the objectives of this research (accounting for the cohort effects of millennials), some new socioeconomic variables were introduced. Millennials represent 39% of the sample, individuals with two jobs 5% and respondents with informal jobs, 3%. A total of 115 individuals (0.5%) indicated that they have informal jobs and reported having two jobs.

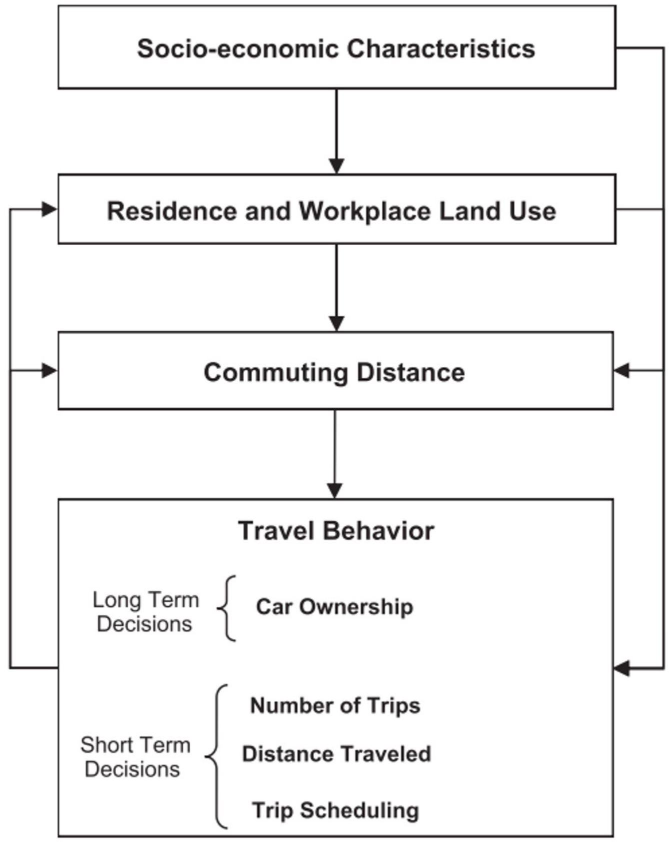

Figure 2. Model's general structure

As stated above, the overall model structure used in the RMSP is the same as that used in Lisbon (de Abreu e Silva, Golob & Goulias, 2006; de Abreu e Silva, Martinez, & Goulias, 2012), Seattle (de Abreu e Silva & Goulias, 2009), Montreal (de Abreu e Silva, Morency, & Goulias, 2012), and SCAG (de Abreu e Silva, Goulias, & Dalal, 2012). The main differences between these studies have mostly to do with the presence or absence of specific variables, as the data used was not specifically collected for them. The proposed framework assumes that socioeconomic characteristics are the only exogenous variables that influence the characteristics of work and residential locations, commuting distance, car ownership, and short-term travel related decisions. Commuting distance and car ownership, which are long-term decisions, mitigate, at least partially, the effects of land-use patterns on the number of trips by mode, distance traveled by mode, and the time spent between the first and last trips, which is equivalent to the height of the space-time prism defined by Hägestrand (1970), creates a link between the model and the activity-based approach and provides information about the individual time budget for out-of-home activities Finally, the possibility of causal relationships is included in order to assess the impact of travel behavior on land use-variables, encompassing possible effects from individual preferences and accounting for self-selection.

Table 1. Sample travel behavior and socioeconomic characteristics

Variables		Average	Std Dev.	Min.	Max.	Frequency (%) 0|1;1|2|3|4|5|6
Socioeconomic characteristic	Age	41.01	13.36	18.00	96.00	-
	Millennials[a]	-	-	0.00	1.00	61|39
	Gender[b]	-	-	0.00	1.00	44|56
	Income	-	-	1.00	6.00	14|13|30|23|15|5
	Household size	6.73	3.74	1.00	35.00	-
	Average Age Household	38.21	13.14	8.33	96.00	-
	Single or Two-Person household	-	-	0.00	1.00	93|7
	Number of workers	1.68	0.77	1.00	10.00	-
	Two jobs[a]	-	-	0.00	1.00	95|5
	Informal worker[a]	-	-	0.00	1.00	97|3
Travel behavior	Time spent between first and last trips (h)	10.68	3.26	0.07	22.83	-
	Km traveled: car	6.83	12.91	0.00	267.85	-
	Km traveled: transit	9.24	15.26	0.00	141.46	-
	Km traveled: non-motorized	0.49	1.44	0.00	32.59	-
	No. of trips: car	1.04	1.46	0.00	12.00	-
	No. of trips: transit	0.91	1.07	0.00	6.00	-
	No. of trips: non-motorized	0.75	1.26	0.00	13.00	-
	No. of car in the household	0.83	0.78	0.00	8.00	-
	Log commuting distance	1.27	1.60	-6.91	5.57	-
Land use indicators - Residence	Residence in traditional urban areas[a]	-	-	0.00	1.00	90|10
	Freeway supply in the residence area[a]	-	-	0.00	1.00	97|3
	Density - home	107.68	71.10	0.38	395.54	-
	Distance CBD—home	14.77	11.08	0.12	82.77	-
	% urban land—home	0.98	0.08	0.11	1.00	-
	% people 400 m from heavy transit—home	0.08	0.15	0.00	1.00	-
	% people 400 m from bus—home	0.90	0.20	0.00	1.00	-
	Access transit/access car—home	0.23	0.13	0.05	1.05	-
	Access nonmot./access car—home	0.93	0.65	0.05	3.85	-
	Accessibility car—home	37.77	9.66	17.45	81.43	-
	Accessibility transit—home	8.47	4.64	1.87	39.16	-
	Mix—home	0.05	0.11	0.00	2.54	-
	Entropy—home	0.03	0.06	0.00	0.60	-
	Km road/person—home	0.01	0.01	0.00	0.09	-
	Freeway supply in the residence area % people 1,000 m from freeway node—home	0.03	0.08	0.00	1.00	-
	Freeway supply in the residence area % people 1,000 m from freeway route—home	0.55	0.39	0.00	1.00	-

<table>
<tr><th></th><th>Variables</th><th>Average</th><th>Std Dev.</th><th>Min.</th><th>Max.</th><th>Frequency (%)
0|1;1|2|3|4|5|6</th></tr>
<tr><td rowspan="14">Land use indicators - Work</td><td>Density—work</td><td>103.27</td><td>70.61</td><td>0.09</td><td>395.54</td><td>-</td></tr>
<tr><td>Distance CBD—work</td><td>11.89</td><td>10.55</td><td>0.03</td><td>85.22</td><td>-</td></tr>
<tr><td>% urban land—work</td><td>0.99</td><td>0.06</td><td>0.00</td><td>1.00</td><td>-</td></tr>
<tr><td>% people 400 m from heavy transit—work</td><td>0.13</td><td>0.20</td><td>0.00</td><td>1.00</td><td>-</td></tr>
<tr><td>% people 400 m from bus—work</td><td>0.92</td><td>0.17</td><td>0.00</td><td>1.00</td><td>-</td></tr>
<tr><td>Access transit/access car—work</td><td>0.23</td><td>0.24</td><td>0.00</td><td>1.22</td><td>-</td></tr>
<tr><td>Access nonmot./access car—work</td><td>0.94</td><td>0.65</td><td>0.00</td><td>7.93</td><td>-</td></tr>
<tr><td>Accessibility car—work</td><td>36.52</td><td>10.92</td><td>0.00</td><td>105.88</td><td>-</td></tr>
<tr><td>Accessibility transit—work</td><td>7.80</td><td>7.23</td><td>0.00</td><td>35.55</td><td>-</td></tr>
<tr><td>Mix—work</td><td>0.10</td><td>0.19</td><td>0.00</td><td>2.91</td><td>-</td></tr>
<tr><td>Entropy—work</td><td>0.06</td><td>0.09</td><td>0.00</td><td>0.84</td><td>-</td></tr>
<tr><td>Km road/person—work</td><td>0.01</td><td>0.01</td><td>0.00</td><td>0.52</td><td>-</td></tr>
<tr><td>Freeway supply in the residence area % people 1,000 m from freeway node—work</td><td>0.04</td><td>0.09</td><td>0.00</td><td>1.00</td><td>-</td></tr>
<tr><td>Freeway supply in the residence area % people 1,000 m from freeway route—work</td><td>0.61</td><td>0.38</td><td>0.00</td><td>1.00</td><td>-</td></tr>
</table>

[a] 1: Yes, 0: No | [b] 0:Woman, 1: Man | [c] Brazilian socioeconomic categories 1 is the highest average income and 6 the lowest. In the model these categories are inverted (6 is the highest income and 1 the lowest).

The plethora of land-use variables was reduced to a smaller set of land-use factors in order to simultaneously capture more efficiently the multidimensionality of urban characteristics while avoiding the potential multicollinearity that may exist between land-use variables. In order to extract the land-use factors, principal components factor analysis (PCA) was used. PCA is a data reduction technique that uses variance to group variables into common factors (Jolliffe, 2002). The resulting factors are introduced as variables into a Path Analysis model, a special case of the Structural Equation Model (SEM). SEM was adopted here because it makes it possible to explicitly model and understand the multiple relationships among a set of variables that can act as predictors and outcomes in the same model (endogenous and exogenous variables) (Bollen, 1989). As SEM is today a relatively commonly used modeling technique in travel behavior analysis, the formulation thereof is not explicitly presented herein. Instead, we direct the reader for some important references, for example, Kaplan (2000) and Bollen (1989). As several endogenous variables in the model are ordinal or censored (car ownership, number of trips, and distances traveled), a Weighted Least Squares (WLS) estimator is used, as it makes it possible to incorporate non-normality. WLS, as implemented in Lisrel, was specifically developed to deal with binary, ordered and censored variables (Golob, 2003). This estimator also has the advantage of producing standardized results (as it uses correlation matrices), allowing for a direct comparison of the effect magnitude. SEM model outputs include direct, indirect, and total effects. Direct effects here are akin to standardized regression coefficients, and total standardized effects are the sum of both direct and indirect effects (effects passed through mediating variables). By examining both direct and total effects, it is possible to identify self-defeating policies, as to look only at direct effects can result in misleading conclusions. Accordingly, if one is to make policy recommendations, it is necessary to look at the total effects. This is particularly important when both the direct and indirect effect coefficients reveal different signs and magnitudes, as indirect effects can dampen or even annul the direct effects, resulting in contrary, smaller or non-significant total effects.

3 Model results and discussion

3.1 Factors and factor loads

Application of PCA to the land-use variables results in seven land-use factors explaining 66% of the total variance. Table 2 shows the results of the seven estimated land-use factors, their main indicators, and respective loads. It is possible to see that the resulting factors help to identify patterns represented by the different land-use aspects.

The first factor, "Working and living in central areas well connected by bus," relates both to individuals working and living near the CBD, in dense, highly urbanized areas that are well served by bus services . The factors "Working in accessible, diverse and central areas" and "Living in a diverse area well supplied by heavy transit" have high loadings as far as entropy and land-use mix variables are concerned, representing, respectively, the diversity of the employment and residence zones, as well as the proximity to heavy (rail-based) transit stations. "Working in accessible, diverse and central areas" also includes gravity-based accessibility measures comparing transit and private cars and nonmotorized transport modes and private cars. The bus service is one of the main defining variables of the factor "Working in an urban area mainly served by bus," which represents working in highly urbanized areas with strong bus service connections and a reduced number of road kilometers per resident. The factor "Working in an area well serviced by freeways" has high loadings in terms of variables representing freeway service in low-density areas. In contrast, the factor "Living in an area well serviced by freeways" captures freeway supply around the residence. Finally, the factor "Living in a highly accessible area" is associated with people living in areas that have relatively high accessibility by transit or nonmotorized modes as compared to accessibility by car.

Table 2. Land-use factors and their defining factor loadings (KMO = 0.766)

Land-use factor	Leading indicators	Loadings
Working and living in central areas well connected by bus	Distance CBD—work	-0.552
	% people 400 m from bus—work	0.501
	Density—Home	0.659
	Distance CBD—Home	-0.656
	% urbanized land—home	0.677
	% people 400 m from bus—Home	0.806
	Km road/person—Home	-0.856
Working in accessible, diverse and central areas	% people 400 m from heavy transit—work	0.705
	Distance CBD—work	-0.499
	Mix—work	0.516
	Entropy index—work	0.559
	Access transit/access car—work	0.780
	Access nonmot./access car—work	0.808
Living in a diverse area well supplied by heavy transit	% people 400 m from heavy transit—Home	0.525
	Mix—Home	0.790
	Entropy index—Home	0.818
Working in an urban area mainly served by bus	% urbanized land—work	0.699
	% people 400 m from bus—work	0.501
	Km road/person—work	-0.855

Land-use factor	Leading indicators	Loadings
Working in an area well serviced by freeways	Density—Work	-0.643
	% people 1,000 m from freeway major node—work	0.531
	% people 1,000 m from freeway routes—work	0.707
Living in a highly accessible area	Access transit/access car—Home	0.707
	Access nonmot/access car—Home	0.785
Living in an area well sserviced by freeways	% people 1,000 m from freeway major node—Home	0.729
	% people 1,000 m from freeway routes—Home	0.665

3.2 Discussion of model results

The SEM estimation allows for the discussion of the results comprising two different aspects: (i) the direct and total effects between exogenous and endogenous variables, as presented in Table 3; and (ii) the direct and total effects between endogenous variables, as presented in Table 4. In these tables, each line represents an equation in the model and the direct and total standardized effects on that variable are presented in the various columns. The model conclusions are considered valid, as the model presents a good fit. The value of the chi-squared statistic is 195, with 151 degrees of freedom. The ratio between these two values is below 2, which is indicative of a good fit (Schermelleh-Engel et al., 2003). Also, the standard Bayesian criteria (AIC and CAIC) indicate that this model is superior to both the independence and the saturated models.

The exogenous variables included in the model (Table 3) show that people with differing socioeconomic characteristics tend to live and work in different areas. This means that, as commonly accepted, the socioeconomic conditions affect individuals' opportunities and can restrict access to various parts of the city. For instance, income is highly important, having direct effects on all the endogenous variables, including all types of land-use patterns. These results show a strong spatial division between households with differing affluence levels, indicating the existence of income-based spatial segregation. As expected, income is also the strongest driver, by far, of household car ownership. The importance of income in explaining location patterns is larger than in the similar models developed for Lisbon, Montreal, SCAG, and Seattle, showing that affordability is a stronger limitation in terms of residential choice in developing countries. With regard to household size, individuals from smaller households (one or two people) tend to live and work in more central, diverse, and accessible areas. A similar effect is observed in the residential location of older households. This fact may reflect that older and more established households tend to live in more consolidated areas, which may be the case because the central areas in São Paulo city are traditional neighborhoods where there is a greater concentration of older residents, resulting from past patterns of urban development and real estate market dynamics. Due to the current conditions of the real estate market, younger households most likely have difficulties in finding affordable housing in these neighborhoods, as housing in areas with lower average commuting times (and, as shown by Table 4, residents in central, diverse and accessible areas tend to have shorter commutes) is more expensive (Acolin & Green, 2017) .

In addition to the socioeconomic variables considered in the previous models, the analysis of the RMSP also studied the influence of individuals working as informal workers or holding two jobs, both of which are more characteristic of economically polarized cities in the Global South. Individuals with two jobs tend to work in accessible urban areas but appear to reside in more outlying areas, which is in line with their long commutes and hints at the fact that they might be unable to afford housing in more central areas. On the other hand, people with informal jobs tend to live and work either in less accessible areas, most likely outlying ones or “work and live in central areas well connected by bus.”. These contradictory results can be explained by the fact that although outlying areas tend to be poorer, there are pockets of poverty and slums in the richer and central areas. “Paraísopolis,” for example, is one of the largest and most famous of such pockets. As job informality is also associated with lower income levels, a common aspect of the location patterns of individuals holding these types of jobs is its reduced commuting distance. This is corroborated by a strong negative effect of holding an informal job on commuting distance. Furthermore, men, people holding two jobs, and wealthier workers tend to work farther away from home. In addition to the economic perspective, other individual characteristics may determine preferences and stimulate behavior. The millennial generation seems to be less car dependent. Households with millennial workers are associated with lower car ownership levels; and being more urbanite than previous generations.

Several patterns arise when analyzing the results involving the short-term travel behavior variables. Women, millennials, and individuals living in low-income and large households are more likely to use nonmotorized modes more often, showing that walking and cycling can be essential transportation modes for vulnerable populations, as can public transportation. Women, millennials, and low-income individuals also tend to rely on public transportation to access their jobs every day. The same is true for people with two jobs, and workers who live in households with more workers or very small households (1-2 people). In contrast, individuals belonging to larger households favor car travel. The standardized direct effect of this variable is negative but indirect effects that include the number of car trips and commuting distance annul it. The result is a positive and statistically significant standardized total effect. As expected, car trips and kilometers traveled by car are also associated with older males with high income.

Millennials also tend to spend more time away from home. This may have to do with more frequent social activities. Individuals working two jobs, individuals with lower income, and those belonging to bigger households tend to have longer elapsed periods of time between their first and last trip. Moreover, in terms of the magnitude of the effects, having two jobs is the biggest determinant for this variable. Longer hours away from home means less time to rest, to conduct or collaborate in in-house activities, and to engage in family life. Accordingly, the implications of holding down two jobs can impact the whole family nucleus, leading to impairments in social, educational and health aspects.

Table 3. Standardized total and direct effects between exogenous and endogenous variables

Exogenous variables **Endogenous variables**	**Type of effect**	**Age**	**Millennial**	**Gender**	**Two jobs**	**Informal job**	**Income**	**House-hold size**	**Household average age**	**Number of workers**	**Single or 2-people household**
Time spent between first and last trips (h)	Direct	**-0.097**		**0.085**	**0.214**	**-0.162**	**-0.130**				**-0.029**
	Total	**-0.077**	**0.004**	**0.094**	**0.21**	**-0.176**	**-0.084**	**0.207**	**-0.011**	**-0.076**	**-0.029**
Km traveled: car	Direct		**0.017**	**0.035**	**-0.096**			**-0.075**			
	Total	**0.053**	0.003	**0.167**	**-0.329**	**-0.017**	**0.262**	**0.150**	**-0.001**	**-0.123**	**-0.027**
Km traveled: transit	Direct			**0.032**			**-0.062**				
	Total	-0.023	**0.018**	**-0.088**	**0.599**	**-0.08**	**-0.149**	0.029	**-0.043**	**0.039**	**0.027**
Km traveled: non-motorized	Direct			**0.018**	**-0.11**	**0.019**					
	Total	0.013	**0.016**	-0.008	**-0.259**	**0.038**	**-0.136**	**0.154**	0.007	**-0.068**	-0.014
No. of trips: car	Direct				**-0.209**	**0.016**	**0.125**	**0.467**		**-0.185**	
	Total	**0.053**	**-0.017**	**0.127**	**-0.362**	0.005	**0.318**	**0.284**	0.003	**-0.145**	**-0.016**
No. of trips: transit	Direct	**-0.086**		**-0.107**	**0.521**	**-0.052**		**0.122**		**0.027**	
	Total	**-0.06**	**0.022**	**-0.13**	**0.602**	**-0.083**	**-0.138**	0.022	**-0.019**	**0.032**	**0.04**
No. of trips: non-motorized	Direct			**0.01**	**-0.091**			**0.278**		**-0.1**	**-0.048**
	Total	0.024	**0.018**	**-0.047**	**-0.301**	**0.056**	**-0.124**	**0.293**	**0.015**	**-0.111**	-0.016
No. of car in the household	Direct	**-0.047**	**-0.049**	**0.073**	**-0.151**	**0.04**	**0.703**	**0.096**	**0.102**	**0.079**	**-0.033**
	Total	**-0.006**	**-0.045**	**0.091**	**-0.085**	0.021	**0.679**	**0.087**	**0.086**	**0.081**	**-0.054**
Log commuting distance	Direct	**-0.052**		**0.087**	**0.513**	**-0.169**	**0.120**	**-0.081**			
	Total	-0.027	**0.002**	**0.089**	**0.537**	**-0.180**	**0.115**	**-0.081**	**-0.015**	**0.001**	**-0.007**
Working and living in central and well connected by bus areas	Direct		**-0.042**	**-0.047**	**-0.016**	**0.017**	**0.164**		**-0.205**	**-0.025**	**0.067**
	Total		**-0.042**	**-0.047**	**-0.016**	**0.017**	**0.164**		**-0.205**	**-0.025**	**0.067**
Working in accessible, diverse and central areas	Direct	**-0.073**		**-0.037**	**0.187**	**-0.082**	**0.175**				**0.069**
	Total	**-0.073**		**-0.037**	**0.187**	**-0.082**	**0.175**				**0.069**
Living in a diverse and well supplied by heavy transit area	Direct	**-0.428**			**-0.174**		**0.124**		**0.368**		**0.085**
	Total	**-0.428**			**-0.174**		**0.124**		**0.368**		**0.085**
Working in an urban area mainly connected by bus	Direct		**-0.028**		**0.111**		**0.042**				
	Total		**-0.028**		**0.111**		**0.042**				
Working in an area well supplied by freeways	Direct			**0.052**	**-0.021**	**-0.066**	**-0.041**		**0.048**		**-0.059**
	Total			**0.052**	**-0.021**	**-0.066**	**-0.041**		**0.048**		**-0.059**
Living in a highly accessible area	Direct	**0.556**	**0.114**		**-0.169**	**-0.057**	**0.399**			**0.066**	**0.067**
	Total	**0.557**	**0.124**	**-0.019**	**-0.151**	**-0.061**	**0.254**	**-0.019**	**-0.018**	**0.049**	**0.079**
Living in an area well supplied by freeways	Direct				**-0.06**		**-0.032**		**-0.038**		**0.022**
	Total				**-0.06**		**-0.032**		**-0.038**		**0.022**

Note: coefficients significant at 95% presented in bold

Although the relationships between endogenous and exogenous variables provide precious insights into how individuals' socioeconomic characteristics affect residence and workplace land use, commuting distance, and travel behavior, the effects between endogenous variables (Table 4) show how such variables are interrelated and how some of them mediate the effects arising from land-use characteristics at the residence and workplace. The results show evidence of longer-term decisions influencing shorter-term ones, highlighting the mediating effects of commuting distance and car ownership on travel patterns. In this aspect, the results align with previous analyses using a similar model framework (de Abreu e Silva, Golob & Goulias, 2006; de Abreu e Silva, Martinez, & Goulias, 2012; de Abreu e Silva & Goulias, 2009). These results also emphasize the robustness of the general modeling framework and prove that it could also be extended to cities in the Global South. In terms of policymaking, it indicates that policies aiming to densify, desegregate land uses, and integrate transit supply in denser areas have a positive effect on travel behavior. These measures could steer trips (and, more importantly, total distances traveled, as this is a more direct indicator of greenhouse gas emissions) away from the car towards more sustainable transportation modes. They also have a positive effect on reducing car ownership and commuting distances, which are strong determinants of mode choice. Indeed, commuting distance seems to be the strongest endogenous determinant of car ownership.

People who live or work in more central, mixed and accessible areas tend to have fewer cars in their households. Living and working in central areas or living in areas well serviced by heavy transit and buses appears to lead to shorter commuting distances. In contrast, workers who work in areas that are well served by freeways or work in central areas but live elsewhere tend to have longer commutes. The high concentration of employment and the scattered residential location in the RMSP demonstrated in other studies (Boisjoly et al., 2017) reveals that central areas attract workers from different parts of the region, thus increasing commuting distance. But "working in accessible, diverse and central areas" is also associated with lower car and higher public transit use. Similar effects are found both in Lisbon, Seattle and Montreal (de Abreu e Silva et al., 2006; de Abreu e Silva, Martinez, L., & Goulias, 2012; de Abreu e Silva, Morency, & Goulias, 2012; de Abreu e Silva & Goulias, 2009). They are evidence of the concentration of jobs in central areas together with a radial transit network structure that provides a high degree of accessibility to the center. Areas that are well served by freeways may be less diverse in terms of their land uses, concentrating more economic activities and fewer residences, thus increasing commuting distances.

People that work and live in more accessible, central, and mixed areas (as well as those better served by public transportation) tend to use nonmotorized modes more frequently. Nevertheless, car ownership and commuting distance are the main determinants of the number of trips by nonmotorized modes. It is possible to identify a slightly similar effect on land-use patterns and travel using public transit modes. The effects of commuting distance and car ownership on public transit use are contradictory. Whereas car ownership has a negative effect, commuting distance has a positive influence on the number of public transit trips. Similar patterns were also found in the models for Lisbon, Seattle, and Montreal (de Abreu e Silva, Golob & Goulias, 2006; de Abreu e Silva, Martinez, & Goulias, 2012; de Abreu e Silva, Morency, & Goulias, 2012; de Abreu e Silva & Goulias, 2009). This positive effect of commuting distance on public transit use has to do with the higher level of public transit accessibility in central areas together with its more radial configuration.

As expected, the model also captures indications of self-selection. Owning more cars can be seen as a manifestation of car ownership and use preferences. Therefore, a negative effect of car ownership on "living in a highly accessible area" is evidence of self-selection, meaning that individuals with strong procar preferences would avoid residing in such areas. This self-selection effect is captured in a very similar way in the models developed for Lisbon, Seattle, and Montreal (de Abreu e Silva, Golob & Goulias, 2006; de Abreu e Silva, Martinez, & Goulias, 2012; de Abreu e Silva, Morency, & Goulias, 2012; de Abreu e Silva & Goulias, 2009). The number of public transit trips has the most substantial effect on reducing car trips, followed by commuting distance and car ownership. This result, evidencing a negative correlation between car and public transit trips, was expected, as they are substitute modes and it is in line with the results obtained in Lisbon and Montreal, but not in Seattle and the SCAG region. This may be attributable to the fact that, in comparison to Seattle and Los Angeles, the cities of Lisbon, Montreal and São Paulo have a more developed public transit network capable of being an alternative to the car. Living and working in central, diverse and accessible areas reduces the number of car trips. However, their magnitude (in terms of total effects) is much smaller when compared to the other variables. The number of trips is the most important variable explaining the distances traveled by mode and, albeit with a smaller magnitude, the number of trips made by the other modes.

Similar to the aforementioned previous models, a high proportion of the effects of land-use patterns on car travel includes car ownership and commuting distances, highlighting the role these long-term decisions have on mediating the effects of land use on shorter-term decisions. The effects of land-use patterns on the distances traveled by mode generally indicate that living and working in more central, dense, mixed, and accessible areas increases the kilometers traveled by nonmotorized modes and public transit and reduces car traveled distances. The magnitude of the effects of land-use patterns is more substantial in reducing the distances traveled by car (as compared to the effect on the number of car trips), suggesting that land-use patterns influence not only modal choices but also reduce average travel distances of car trips. In terminating this discussion of the results, it must be mentioned that the total time elapsed between the first and last trips is influenced mainly by the distances traveled by public transit, the number of trips by car, and commuting distance. The total effects of land-use patterns result from indirect effects, including the trips and distances traveled by mode and commuting distance.

4 Conclusions

This paper uses SEM to analyze the influence of land-use patterns on travel behavior in the Metropolitan Area of São Paulo. The adopted model structure accounts for self-selection and residential sorting effects. It models the hierarchy of travel-related decisions, which range from long-term decisions, such as commuting distance, and car ownership, to short-term decisions, such as the number of trips by mode, distance traveled by mode, and the time spent between the first and last trips. This framework was first used in a model developed for Lisbon and later employed in Seattle, Montreal, and the SCAG region. In all of these previous applications, the model structure held: The main conclusion that land-use patterns, both in the area of residence and that of employment, significantly influences travel behavior, which is partly mediated by commuting distance and car ownership, is in line with all the previous studies. A similar overall conclusion can be made for the present application.

It is possible to say that the model structure holds for the biggest Latin America metropolitan region. Thus, the results support the claim that land-use policies could steer mobility towards a more sustainable path even in cities in the Global South. The results also highlight the need to integrate the supply of public transportation within the broader range of land-use policies. Nevertheless, there are some results in the model that evidence the particularities of the São Paulo region. One output that differs greatly from the previous models is the impact of household income levels. The income strongly impacts residence location patterns, clear evidence of economic-based spatial segregation. In the Global South, and especially in Latin American countries, income can serve as a strong barrier in terms of choosing where to live and also restrict work opportunities, creating spatial segregation between low and

Table 4. Standardized total and direct effects between endogenous variables

Exogenous variables **Endogenous variables**	**Type of effect**	**Km traveled: transit**	**No. of trips: car**	**No. of trips: transit**	**No. of trips: nonmotorized**	**No. of car in the household**	**Log commuting distance**	**Working and living in central and well connected by bus areas**	**Working in accessible, diverse and central areas**	**Living in a diverse and well supplied by heavy transit area**	**Working in an urban area mainly connected by bus**	**Working in an area well supplied by freeways**	**Living in a highly accessible area**	**Living in an area well supplied by freeways**
Time spent between first and last trips (h)	Direct	**0.381**	**0.425**		**0.259**									
	Total	**0.381**	**0.425**	**0.090**	0.015	-0.005	**0.072**	0.000	**0.013**	**-0.031**	**-0.005**	**0.004**	**0.034**	**-0.012**
Km traveled: car	Direct		**0.848**				**0.197**		**-0.172**					
	Total		**0.848**	-0.566	**-0.306**	**0.243**	**0.503**	**-0.059**	0.208	**-0.110**	**0.009**	**0.040**	**-0.038**	**-0.029**
Km traveled: transit	Direct			**0.983**		**0.087**				**-0.085**				
	Total			**0.983**	**-0.237**	**-0.198**	**0.073**	**0.045**	**0.057**	**-0.036**	**-0.036**	**-0.002**	**0.081**	**0.004**
Km traveled: non-motorized	Direct		**-0.162**	**-0.136**	**0.757**	**-0.045**	**0.183**							
	Total		**-0.162**	**-0.028**	0.848	**-0.203**	**-0.209**	**0.023**	**0.066**	0.092	**0.006**	**-0.020**	**0.062**	**0.009**
No. of trips: car	Direct			**-0.668**	**-0.522**		**0.185**						**0.055**	**-0.029**
	Total			**-0.668**	**-0.361**	**0.286**	**0.361**	**-0.060**	-0.060	0.113	**0.016**	**0.032**	**-0.045**	**0.035**
No. of trips: transit	Direct				**-0.241**	**-0.316**		**0.031**	**0.061**	**0.054**	**-0.035**		**0.103**	
	Total				**-0.241**	**-0.290**	**0.065**	**0.053**	**0.063**	**0.059**	**-0.037**	**-0.006**	**0.082**	**0.006**
No. of trips: non-motorized	Direct					**-0.182**	**-0.401**		**0.085**	**0.070**			**0.087**	
	Total					**-0.200**	**-0.423**	**0.034**	**0.064**	**0.119**	**0.009**	**-0.033**	**0.087**	**0.004**
No. of car in the household	Direct						**0.111**	**-0.085**	**-0.060**	**-0.091**		**0.035**		**-0.020**
	Total						**0.111**	**-0.090**	**-0.051**	**-0.099**	**-0.003**	**0.042**		**-0.020**
Log commuting distance	Direct							**-0.040**	**0.078**	**-0.071**	**-0.022**	**0.062**		
	Total							**-0.040**	**0.078**	**-0.071**	**-0.022**	**0.062**		
Living in a highly accessible area	Direct					**-0.214**								
	Total					**-- 0.214**	**-0.024**	**0.019**	**0.011**	**0.021**	**0.001**	**-0.009**		**0.004**

Note: coefficients significant at 95% presented in bold high-income individuals. Accordingly, the implementation of land-use policies should incorporate components that tackle the unequal distribution of opportunities and promote affordable housing programs in public transit-accessible areas, with the aim of reducing car dependence and commuting distance for public transit users. Otherwise, there is a risk that land-use policies might increase spatial segregation and gentrification of the denser, accessible, and mixed areas.

The model, by explicitly incorporating cohort effects, namely, controlling if the respondent is a millennial or not, makes it possible to draw some conclusions about said group's behavior. Overall, the results are aligned with previous research on millennials. They own less cars and use public transit and nonmotorized modes more frequently. These results allow for the conclusion that Brazilian millennials follow the same trends identified in the same cohort in other countries of the Global North. These results are helpful, as they indicate the possibility of a change in preferences towards more sustainable transport modes and denser and more diverse urban environments.

This study has also its limitations. One limitation has to do with the nature of the data used. As attitudinal variables relating to preferences and lifestyles are not included, self-selection effects are mostly captured via the effects of socioeconomic variables and car ownership levels. Including attitudinal variables in the framework would be an improvement. The second limitation has to do with the fact that the study did not have data on travel pass ownership, which is an important long-term intermediate variable that was included in the original model framework (de Abreu e Silva, Golob & Goulias, 2006). Another limitation is related to the fact that the data used in this study is cross-sectional, which restricts the conclusions that can be drawn about causality. Finally, whilst they are controlled by diverse socioeconomic variables, millennials are treated herein as a homogenous category. Recent research (Groth et al., 2021) highlights the existence of strong sociocultural heterogeneities among millennials, with significant implications for their travel patterns. This is a topic of research that could be explored further within the context of Global South Cities.

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