Income and commute satisfaction: On the mediating roles of transport poverty and health conditions

Abstract: Due to financial constraints, it can be expected that low-income groups may encounter transport poverty (e.g., limited travel mode options, low accessibility to workplaces) and have poor health conditions, therefore making them feel unsatisfied with commuting. However, few previous studies have examined this assumption. Using data derived from a face-to-face survey performed in 2019 in Chengdu (China), we aim to verify whether low-income commuters are less satisfied with commuting and how this is related to transport poverty and health conditions. Structural Equation Modeling is used to quantify both direct and indirect effects of income on commute satisfaction, leading to the three major findings. First, due to limited access to cars, people with low incomes are more likely to choose public transit for commuting and indicate more traffic congestion. Consequently, they tend to have long commute durations and are less likely to be satisfied with commuting. Second, high-income groups are more likely to use private cars for commuting, which also leads to a high level of congestion, long commute durations, and low commute satisfaction. Third, low-income groups are more likely to have poor health conditions, making them have long commute durations and feel unsatisfied with commuting.

Keywords: Commute satisfaction; low-income groups; transport poverty; health conditions; Chengdu (China)

1 Introduction

Given that commuting accounts for a high share of daily trips, commute satisfaction is considered relevant to people's quality of life (Chatterjee et al., 2020). However, low-income populations may hardly be satisfied with commuting for two reasons. First, low-income people tend to experience transport poverty (e.g., lower availability of transport opportunities, the lack of access to places of interest) due to financial constraints (Titheridge et al., 2014; Stoke & Lucas, 2011). Prior research has confirmed that transport poverty is a cause of low commute satisfaction (e.g., Hook et al., 2021; Wang et al., 2021). Second, low-income populations usually have health problems mainly because of limited health services, high-quality food, and physical activities (Khullar & Chokshi, 2018). The poor health conditions may make commute trips more difficult and uncomfortable, leading to low commute satisfaction (Ye & Titheridge, 2019).

Previous studies have particularly paid attention to the topic of commute satisfaction and investigated the determinants of commute satisfaction (e.g., Ettema et al., 2011, 2012, 2013; Friman et al., 2017; Mao et al., 2016; Singleton, 2019; Ye & Titheridge, 2017, 2019; Ye et al., 2020). However, little research focuses on whether and how the satisfaction with commuting varies across income distributions. Against this background, we aim to examine the relationship between income and commute satisfaction and particularly reveal the mediating roles of transport poverty and health conditions in this relationship. In the present study, the data are derived from a face-to-face survey in 2019 in Chengdu, China. The remainder of this paper is organized as follows. In Section 2, related previous studies are briefly summarized. Methodologies are introduced in Section 3, followed by analytical results in Section 4. Conclusions and discussion are presented in the final section.

2 Literature review and conceptual analyses

2.1 Literature review

In the past decade, numerous studies have conceptually and/or empirically explored the issue of commute satisfaction. Most of them focus on the factors influencing commute satisfaction. Travel mode choice is found to be a crucial factor. It is widely confirmed that commuting by active modes (e.g., cycling and walking) positively contributes to commute satisfaction, while commuting by public transit has negative impacts on commute satisfaction (e.g., De Vos et al., 2016; Friman et al., 2017; Lades et al., 2020; Morris & Guerra, 2015a; Singleton et al., 2019; St-Louis et al., 2014). Meanwhile, some researchers reveal that the preference for travel modes (i.e., travel attitude) is also associated with commute satisfaction. For instance, Ye and Titheridge (2017) indicated that commuters with higher preference for walk, transit, and car tend to report higher levels of commute satisfaction. Furthermore, some scholars further investigated the influence of the mismatch between preferred and chosen travel modes on commute satisfaction. A consensus is that people commuting by their preferred modes are more likely to be satisfied with commuting (St-Louis et al., 2014; Ye & Titheridge, 2019; Ye et al., 2020).

Besides travel mode, other trip characteristics are also found to have influences on commute satisfaction. The length of commuting is frequently examined. It is often confirmed that longer commute durations and an increase in commute durations after relocations tend to result in a lower level of commute satisfaction (e.g., De Vos et al., 2019; Ettema et al., 2012, 2013; Gerber et al., 2020; Higgins et al., 2018; Manaugh & El-Geneidy, 2013; Morris & Guerra, 2015b; Singleton et al., 2019; Wang et al., 2020). In addition, some scholars explored the roles of road congestion, in-vehicle crowding, and waiting time for transit. As expected, higher levels of road congestion and in-vehicle crowding, and longer waiting time are often negatively correlated with commute satisfaction (e.g., Ettema et al., 2013; Higgins et al., 2018; Lunke, 2020; Smith, 2017; Ye & Titheridge, 2017). Notably, in-vehicle crowding and waiting time for transit are often used to predict commute satisfaction of public transit users.

Additionally, some studies explore the influence of built environment elements on commute satisfaction, however leading to inconsistent findings. For example, Mao et al. (2016) found that people residing in urban areas (compared to suburban areas) tend to be more satisfied with commuting by cycling and metro in Beijing, China. Similarly, Mouratidis et al. (2019) indicated that – in Oslo metropolitan area, Norway – shorter distances from home to the city center, higher residential density, and compact inner-city areas (compared to sprawled suburban areas) are positively correlated with a higher level of commute satisfaction. Using data collected from Sweden and Xi'an city (China), respectively, however, both Ettema et al.

(2012) and Ye and Titheridge (2019) revealed insignificant associations between built environment elements and commute satisfaction. In another study by Ye and Titheridge (2017), they indicated indirect effects of the built environment on commute satisfaction through travel model choices and the characteristics of the trip (e.g., road congestion).

Moreover, physical health is considered as another factor influencing commute satisfaction in a few studies. Smith (2013) revealed that higher levels of self-reported health are positively correlated with commute satisfaction in Portland, the US. Subsequently, Mokhtarian et al. (2015), analyzing satisfaction with daily travel in France, found that health problems had a positive effect on finding travel tiring and unpleasant. Using data collected data from Xi'an, China, Ye and colleagues also confirmed the positive association between better health conditions and higher commute satisfaction (Ye & Titheridge, 2017, 2019; Ye et al., 2020).

In sum, the determinants of commute satisfaction have been explored in a number of existing studies. However, these studies provide "*limited understanding of how commute satisfaction varies across the socio-economic status distribution*" (Chatterjee et al., 2020, p.24). In particular, low-income groups may be less likely to be satisfied with commuting because of transport poverty and poor health conditions. An in-depth exploration of their commute (dis)satisfaction is helpful to create policy recommendations for the development of urban inclusive transportation systems. To the best of our knowledge, however, only a study by Ye and Titheridge (2019) specifically revealed the influential factors of commute satisfaction among low-income groups in Xi'an, China. They revealed that low-income commuters have a lower level of commute satisfaction than high-income commuters but failed to empirically examine why.

2.2 Conceptual analyses

Inspired by previous studies, we assume that commute (dis)satisfaction of low-income groups may be closely correlated with the following two aspects.

The first aspect is transport poverty. Transport poverty is a broad concept consisting of at least three sub-dimensions: (1) *mobility poverty* – referring to a lack of transportation and mobility options; (2) *accessibility poverty* – referring to a lack of access to destinations and participation in basic daily activities; (3) *transport unaffordability* – referring to a lack of individual resources to afford transportation options (Lucas et al., 2016). Given the elaboration on the concept, it is reasonable to consider transport poverty as a potential explanation for low commute satisfaction of low-income populations. For example, because of financial constraints, low-income commuters can hardly afford to purchase and run a car. Meanwhile, they may tend to reside in weakly urbanized areas with low accessibility to transit stations and workplaces (Lucas et al., 2016; Zhao, 2015). This means that low-income commuters may be more likely to witness transport poverty and have fewer transport options for commuting, leading to lower commute satisfaction (Ye & Titheridge, 2019).

However, two plausible hypotheses are conflicting with the assumption that low-income people have fewer transport options. The first states that low-income populations may be "forced" to own a car, because they usually live far away from the urban center and must travel long distances in daily life (Currie & Senbergs, 2007; Curl et al., 2018; Zhao, 2015). The second postulates that low-income groups may tend to reside or work in areas with high accessibility to transit, because they have a low level of car ownership (Baum-Snow et al., 2005; Dawkins & Moeckel, 2016; Glaeser et al., 2008). Both hypotheses are reasonable but may depend on local contexts such as prices of cars, fuel, and housing. For example, in a country or a city with low prices of cars and fuel but a high price of housing, low-income people may choose to own a car rather than to reside in densely urban areas and vice versa. Therefore, in the two situations mentioned above, low-income people may not necessarily encounter limited transportation options, implying that they may not be less satisfied with commuting than high-income people.

The second aspect refers to poor health conditions. Compared to trips for other purposes, commutes usually require more physical strength because of fixed workplaces and working hours. People with poor health conditions may experience more difficulty in commuting and be unsatisfied as a result. Existing studies have confirmed a negative association between poor health conditions and commute satisfaction (Mokhtarian et al., 2015; Smith, 2013; Ye & Titheridge, 2017, 2019; Ye et al., 2020). This situation may be more likely to occur among low-income populations, because they tend to have poor health conditions for the following reasons (Benzeval & Judge, 2001; Khullar & Chokshi, 2018): (1) They lack access to high-quality health services; (2) They tend to have risk behaviors like smoking and drinking; (3) Their housing conditions are relatively poor (e.g., lack of housing spaces); (4) They are more likely to reside in neighborhoods with a high density of tobacco retailers and fast-food restaurants but with limited open spaces for physical activities. Notably, transport poverty can impose barriers to travel for low-income people to use health care services, get fresh food, and access open spaces for physical activities, which may result in poor health conditions and thus reduce commute satisfaction.

In sum, we hypothesize that transport poverty and poor health conditions are the main factors influencing commute satisfaction for low-income people. The following two sections will empirically examine whether and how income indirectly influences commute satisfaction through transport poverty and health conditions.

3 Data

3.1 Data sources

The data used in the present study are mainly derived from a face-to-face survey on travel behavior between June 30th and August 1st 2019 in Chengdu, China. Chengdu is the capital city of Sichuan Province in China. By 2020, a total of 20.94 million people resided in the city, and 16.49 million (accounting for 78.8%) were urban residents. This survey was performed with a two-stage sampling approach. First, the sampled neighborhoods were determined. In Chengdu, the main urban area was divided into five zones by four ring roads. The zones closer to the city center tended to be more strongly urbanized. In this circumstance, 5-7 residential neighborhoods were geographically randomly selected from each zone. In the end, a total of 29 neighborhoods were used as the sampled units (see Figure 1). Second, respondents were recruited by randomly knocking on doors and/or approaching people at public spaces in these neighborhoods. Residents aged 16 or above were considered as the target population. A face-to-face interview was conducted with each respondent. A paper-based questionnaire was used to record their answers. After respondents finished the survey, a pack of handkerchief papers or a fan was provided as an incentive for their participation. In the end, a total of 1011 residents participated in the survey. After leaving out respondents who were not employed or those who did not respond to commute satisfaction scales, we obtain 618 valid records for the present study (see Table 1). Notably, this survey was not designed exclusively for commuting but for travel in general (including commuting). This is why non-employees were also invited to participate.

In addition to the survey, the points of interest (i.e., POI) from Map.Baidu.com are used as another data source. Map.Baidu.com is one of the most used e-maps in China. On November 16th 2017, we collected the POI data regarding bus and metro stations across the Chengdu city. Notably, a period gap of around one and a half years exists between the POI data and the survey data. To our knowledge, there were limited changes in bus stations during this period, while Chengdu started operating a few new metro lines. To address this issue, we manually updated the POI data on metro stations till August 2019. For each POI, we obtained its name and coordinate information. The POI data are then used to assess public transport poverty.

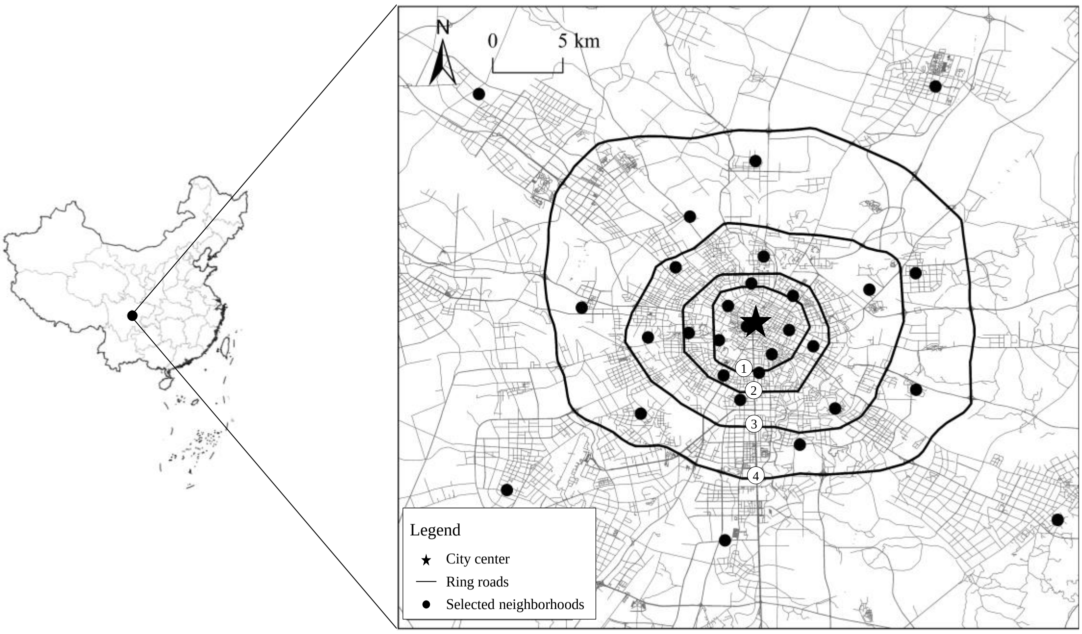


Figure 1 Study area (Chengdu, China) and sampled neighborhoods

3.2 Measurement of income

Prior research often uses either household income (e.g., Benzeval & Judge, 2001; Zhao, 2015) or personal income (e.g., Ye & Titheridge, 2019) to distinguish between low- and high-income groups, while little considers both. To address this limitation, both household and personal incomes are included in the present study. In this survey, respondents' annual household income was measured on a seven-point scale, and monthly individual income was measured on a four-point scale (see Table 1).

Table 1 Basic characteristics of valid respondents

Variables	Categories	N/Mean	Percent/S.D.
Gender	Male	295	47.7%
	Female	323	52.3%
Age (years)	20 or younger	43	7.0%
	21-30	369	59.7%
	31-40	153	24.8%
	Older than 40	53	8.6%
Education	High school or less	84	13.6%
	Colleges/technical school	231	37.4%
	Undergraduate school	248	40.1%
	Graduate school or more	55	8.9%
Household size	Number of household members	3.2	1.6
Household annual income (Yuan)	50,000 or lower	62	10.1%
	50,001-100,000	160	26.0%
	100,001-150,000	146	23.7%
	150,001-200,000	118	19.2%
	200,001-300,000	57	9.3%
	300,001-400,000	38	6.2%
	Higher than 400,000	35	5.7%
Individual monthly income (Yuan)	4,000 or lower	174	28.2%
	4,001-6,000	177	28.7%
	6,001-8,000	141	22.9%
	Higher than 8,000	125	20.3%

Note: 1 Yuan was around US $ 0.145 in 2019.

3.3 Measurement of commute satisfaction

In previous studies, various methods are used for the measurement of commute satisfaction (Chatterjee et al., 2020). Among them, the satisfaction with travel scale (STS) designed by Ettema et al. (2011) is widely adopted by researchers. Following Ettema et al. (2011), the STS including nine statements was introduced in the survey. This scale asked respondents to what extent they experienced certain affective emotions during their most recent commute and how they evaluated this commute:

- Time pressed – relaxed;
- Worried I would not be in time – confident I would be in time;
- Stressed – calm;
- Tired – alert;
- Bored – enthusiastic;
- Fed up – engaged;
- Commuting was worst – best I can think of;
- Commuting was low – high standard;
- Commuting worked poorly – worked well.

All answers were measured on a seven-point scale (from -3, representing negative emotions/evaluations, to +3, representing positive emotions/evaluations). In order to fully depict the process of commuting, the satisfaction with commuting to and from work was measured separately. The Cronbach's alpha coefficients of the satisfaction scale for commuting to and from work are respectively 0.94 and 0.95. This means that the nine statements have good internal consistency. Therefore, the average scores of these statements are calculated to reflect the overall satisfaction of a respondent with commuting to and from work, respectively.

Figures 2-3 show the commute satisfaction levels by income groups, revealing an overall trend that low-income people are less satisfied with commuting than higher-income people. This is consistent with our expectations and previous studies (e.g., Ye & Titheridge, 2019). However, the level of commute satisfaction first increases with incomes rising then decreases somewhat after middle incomes, but finally reaches the highest values. In other words, commute satisfaction tends to be low not only for low-income groups but also for middle-high-income groups. This implies a complex relationship between income and commute satisfaction.

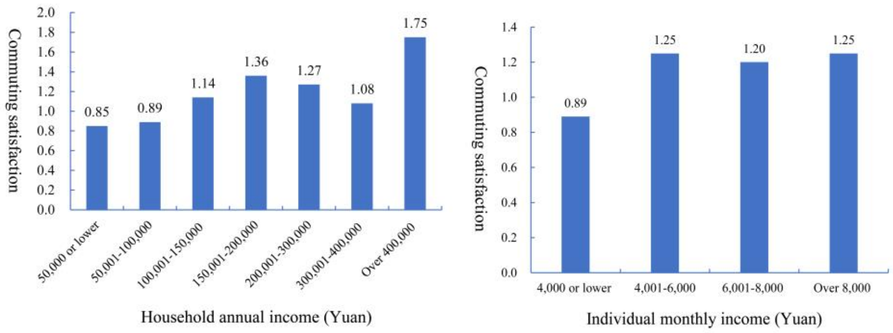


Figure 2 Overall satisfaction with commuting to work by income levels

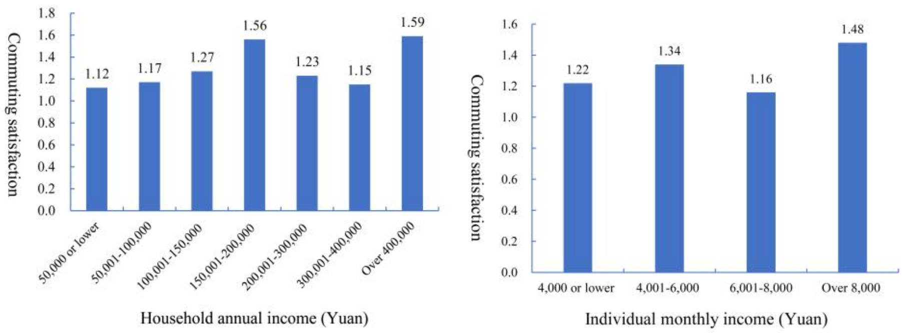


Figure 3 Overall satisfaction with commuting from work by income levels

3.4 Measurement of transport poverty

According to the concept mentioned above, transport poverty can be measured in three aspects: mobility poverty, accessibility poverty, and transport unaffordability (Churchill & Smyth, 2019). Notably, compared to the former two, transport unaffordability is harder to measure. Researchers commonly use the share of actual transport expenditure in income as an indicator of transport unaffordability (Lucas et al., 2016). However, this measurement method has received many critiques because some researchers found that high-income people are likely to spend a higher share of incomes on transport than low-income people (Stoke & Lucas, 2011; Titheridge et al., 2014). Therefore, the present study will measure transport poverty with a particular focus on mobility poverty and accessibility poverty.

Following previous studies (Lucas et al., 2016; Stoke & Lucas, 2011; Titheridge et al., 2014), the availability of both car use and public transit services is employed to represent mobility poverty (see Table 2). The availability level of car use is indicated by the household car ownership, which is measured on an ordinal scale. Accessibility to public transit is reflected by the number of bus and metro stations within a certain buffer distance from home and workplaces, which are calculated with POI data in ArcGIS. The buffer distance is set to 800 m in the present study, because the maximum access distance by walking is around 800 m for most residents in Chinese large cities (Pan et al., 2010). A preliminary check shows that the number of bus and metro stations are highly correlated, which will be problematic (e.g., severe multicollinearity) in the following quantitative analysis. To address this issue, a public transit index (PTI) is constructed for residences and workplaces, separately:

$$PTI_i = Norm(BS)_i + Norm(MS)_i;$$
$$Norm(BS)_i = (NBS_i - NBS_{min})/(NBS_{max} - NBS_{min});$$
$$Norm(MS)_i = (NMS_i - NMS_{min})/(NMS_{max} - NMS_{min})$$

where PTI_i represents the public transit index of individual *i*; $Norm(BS)_i$ and $Norm(MS)_i$ respectively represent the normalized values of the number of bus stations and metro stations for individual *i* following the principle of Max-Min normalization; NBS_i and NMS_i respectively represent the number of bus stations and metro stations within a buffer distance of 800 m for individual *i*; NBS_{min} and NMS_{min} respectively represent the minimum number of bus stations and metro stations within the buffer distance across all valid respondents; NBS_{max} and NMS_{max} respectively represent the maximum number of bus stations and metro stations within the buffer distance across all valid respondents.

Accessibility to workplaces is employed as the indicator of accessibility poverty (see Table 2), which is measured in two ways: the straight-line distance between residences and workplaces (i.e., commute distance) and the self-reported time spent on the most recent commute to and from work (i.e., commute durations).

3.5 Measurement of health conditions

According to Hansson et al. (2011), a measurement scale including seven questions is used to measure the self-reported health of respondents:

- How do you physically feel right now when thinking about your health?
- How do you psychologically feel right now when thinking about your health?

- Have you felt stressed recently in your everyday life?
- Have you felt full of pep recently?
- Have you had a lot of energy recently?
- Have you felt worn out recently?
- Have you felt tired recently?

The answers range from “very poor (1)” to “excellent (5)” for the first two questions and from “not at all (1)” to “always (5)” for the last five questions. These statements are potentially correlated with each other. A factor analysis with principal axis factoring and Promax rotation is employed to reduce dimensions, which helps avoid severe multicollinearity in the following models. Consistent with the widely accepted practice (Costello & Osborne, 2005), the principle of eigenvalues-greater-than-1 is applied, leading to three factors retained: exhaustion, energetic, and self-rated health (see Appendix A). 73.2% of the total variance is explained by the three factors. The scores of the three factors are used to quantify health conditions.

3.6 Control variables

According to previous studies analyzing the determinants of commute satisfaction, four categories of control variables are used in the present study. The first is sociodemographic factors including respondents’ gender, age, educational attainments, and household size. Gender is transformed into a binary variable, while age and educational levels are measured on an ordinal scale (see Table 1). The second refers to travel mode choice. Respondents were asked to report the transport mode that was used for the longest duration for their most recent commutes to and from work, respectively. The third is self-reported traffic congestion. In the survey, all respondents were asked to indicate the experienced level of traffic congestion during commuting to and from work, respectively. The answer was set on a five-point scale ranging from “not at all congested (1)” to “extremely congested (5)”. The measurements for mode choice and traffic congestion are reported in Table 3.

The fourth refers to travel attitudes. In analogy with Cao (2015) and Handy et al. (2005), sixteen statements are used to measure travel attitudes. Respondents could indicate to what extent they agreed on these statements on a five-point scale from “strongly disagree (1)” to “strongly agree (5)”. Similarly, a factor analysis with principal axis factoring and Promax rotation is employed to reduce dimensions. The principle of eigenvalues-greater-than-1 is also applied to extract four factors: pro-sustainable modes, safety of car, pro-car, and status of car, explaining 53.4% of the total variance (see Appendix B). The scores of the four factors are used as the quantification of travel attitudes.

Notably, some specific characteristics of commuting by public transit (e.g., in-vehicle crowding, waiting time) are also found to be influential in commute satisfaction. Nonetheless, we will not consider them as control variables partly because commuting by public transit is not the particular focus in the present study.

Table 2 Indicators of transport poverty

Indicators	Descriptions	N			Percent	
Household car ownership	No car	224			36.2%	
	One car	335			54.2%	
	Two or more cars	59			9.5%	
		N	Max	Min	Mean	S.D.
Commute distance (In kilometer)	Straight-line distance between residences and workplaces	534	7.75	0.00	5.63	8.19
Commute durations (In minute)	Commute to work	612	180	2	29.13	21.43
	Commute from work	608	180	2	30.52	21.99
Built environment around residences						
Accessibility to metro stations	Number of metro stations within an 800 m radius of home	592	3	0	0.51	0.79
Accessibility to bus stations	Number of bus stations within an 800 m radius of home	592	38	0	10.79	8.56
Public transit index	Weighted index with number of metro and bus stations around residences	592	1.47	0.00	0.45	0.40
Built environment around workplaces						
Accessibility to metro stations	Number of metro stations within an 800 m radius of workplaces	551	3	0	0.69	0.87
Accessibility to bus stations	Number of bus stations within an 800 m radius of workplaces	551	41	0	12.62	8.98
Public transit index	Weighted index with number of metro and bus stations around residences	551	1.66	0.00	0.54	0.43

Table 3 Mode choice and congestion

Commutes	Variables	Descriptions	N	Percent
Commute to work	Travel mode choice	Private car	113	18.4%
		Public transit (i.e., bus & metro)	238	38.8%
		Active mode (i.e., cycling & walking)	263	42.8%
	Congestion	Not at all congested	200	32.6%
		Slightly congested	241	39.3%
		Somewhat congested	95	15.5%
		Moderately congested	65	10.6%
		Extremely congested	13	2.1%
Commute from work	Travel mode choice	Private car	112	18.3%
		Public transit (i.e., bus & metro)	239	39.1%
		Active mode (i.e., cycling & walking)	261	42.6%
	Congestion	Not at all congested	191	31.3%
		Slightly congested	217	35.5%
		Somewhat congested	114	18.7%
		Moderately congested	76	12.4%
		Extremely congested	13	2.1%

3.7 Modeling strategy

Structural equation modeling (SEM) is applied in the present study because we consider multidimensional factors and will particularly examine the mediating roles of transport poverty and health conditions. In the SEM framework, sociodemographic factors (including income levels) are employed as exogenous variables. Other factors are treated as endogenous variables that are potentially influenced by sociodemographic factors. Meanwhile, some possible causal relationships are expected in theory between these endogenous variables. First, all endogenous variables are expected to influence satisfaction. Second, travel attitudes, car ownership, public transit accessibility, and commute distance are expected to impact travel mode choice. Third, commute distance, travel mode choice, and traffic congestion are expected to have impacts on commute duration. Fourth, travel mode choice is expected to influence traffic congestion (See Figure 4 for details).

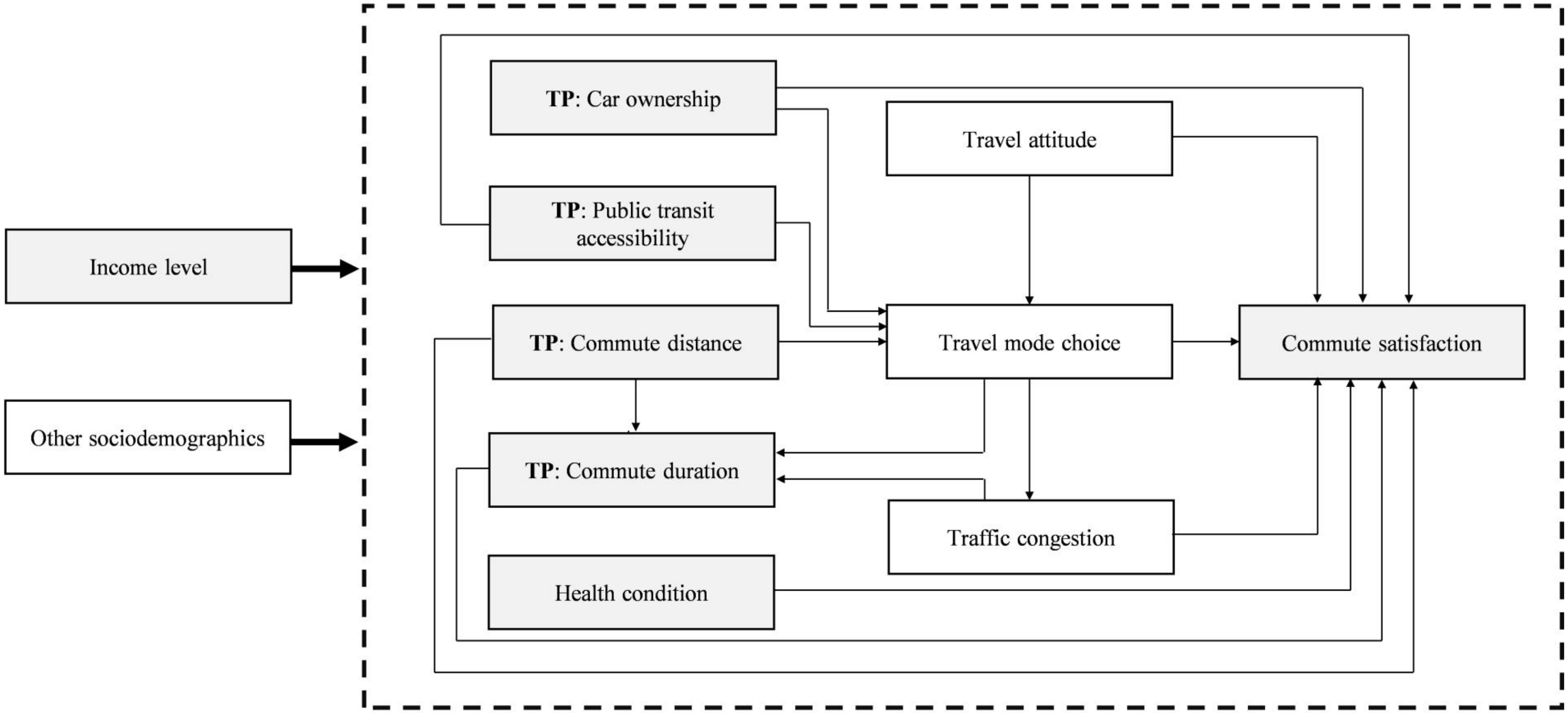
Following Figure 4, we develop four initial SEMs that examine the relationships between (1) household income and satisfaction with commuting to work (named "Model 1"), (2) individual income and satisfaction with commuting to work (named "Model 2"), (3) household income and satisfaction with commuting from work (named "Model 3"), and (4) individual income and satisfaction with commuting from work (named "Model 4"), respectively. The former two models use 617 respondents who responded to the STS for commuting to work, the latter two models use 614 who responded to the STS for commuting from work. In all models, active modes are employed as a reference category for the variable of travel mode choice. Notably, some values of explanatory variables are missing for some respondents[1]. To avoid a substantial reduction in the sample size, we do not remove these respondents. A full information maximum likelihood (FIML) method is

[1] The number of valid records for all explanatory variables are reported (see Tables 1-3 and Appendix A and B), so that readers can clearly see how many values are missing for each.

widely considered superior and unbiased for estimations with missing data (Enders & Bandalos, 2001) and is therefore applied in the present study.

Generally, FIML requires data to meet the assumption of multivariate normal distribution. Nonetheless, this approach is also considered quite robust against violations of multivariate normality in transportation research when the sample size is at least 200, at least 15 times the number of the observed variables, and at least 5 times the number of free parameters estimated (Golob, 2003). In each of the four initial models, a total of 20 observed variables are included, and 170 free parameters are estimated. Apparently, the requirement for sample size according to the number of free parameters is not satisfied. To address this problem, we manually remove all links that are not statistically significant (at $p>0.10$) following the backward stepwise principle (e.g., Ma & Cao, 2019; Shi et al., 2021). During the pruning process, a variable will be deleted once it has neither a direct nor an indirect link with commute satisfaction. In the end, the public transit index around residences and the health variable "*exhaustion*" are removed from both Models 1-2. The two health variables "exhaustion" and "*energetic*" are removed from both Models 3-4. Meanwhile, the public transit index around residences is also removed from Model 3. The number of free parameters in the four models decreases to 89-94, meaning that the ideal sample size should not be lower than 470. It can therefore be expected that the sample size in the present study (N=617 and N=614) is sufficient in these pruned models for robust results.

Moreover, goodness-of-fit tests suggest that the four initial models do not fit data well, requiring model modifications. Making residuals of endogenous variables correlated is a commonly used modification method in SEM (Lei & Wu, 2007). In line with the widely adopted method, we add correlations between residuals of endogenous variables following two principles. First, the correlations should be theoretically justifiable, which helps avoid models with nonsensical outcomes (Lacobucci, 2009). Second, the number of correlations should be as small as possible, which helps reduce estimation bias to the largest extent (Lei & Wu, 2007). Consequently, goodness-of-fit tests indicate a reasonable fit (i.e., CFI>0.90, RMSEA<0.06) after we manually create six correlations between residuals of endogenous variables for each model. These correlations are between residuals of two travel mode choices (i.e., private car and public transit), two indicators of public transit accessibility (i.e., public transit index around residences and workplaces), two indicators of health conditions (i.e., energetic and self-reported health), and three pairs of travel attitudes (i.e., pro-sustainable modes and status of car, safety of car and pro-car, and safety of car and status of car). These added correlations are reasonable. For example, normally people do not use private cars for commuting when they choose public transit, and vice versa. Hence, a correlation between them can be reasonably expected. People who care more about accessibility to public transit services may be more likely to both reside and work in areas with a high density of transit stations. Therefore, public transit index around residences and workplaces are expected to be correlated with each other.



Note: "TP" represents "Transport Poverty"; ☐ represents variables of interest.

Figure 4 Modeling framework

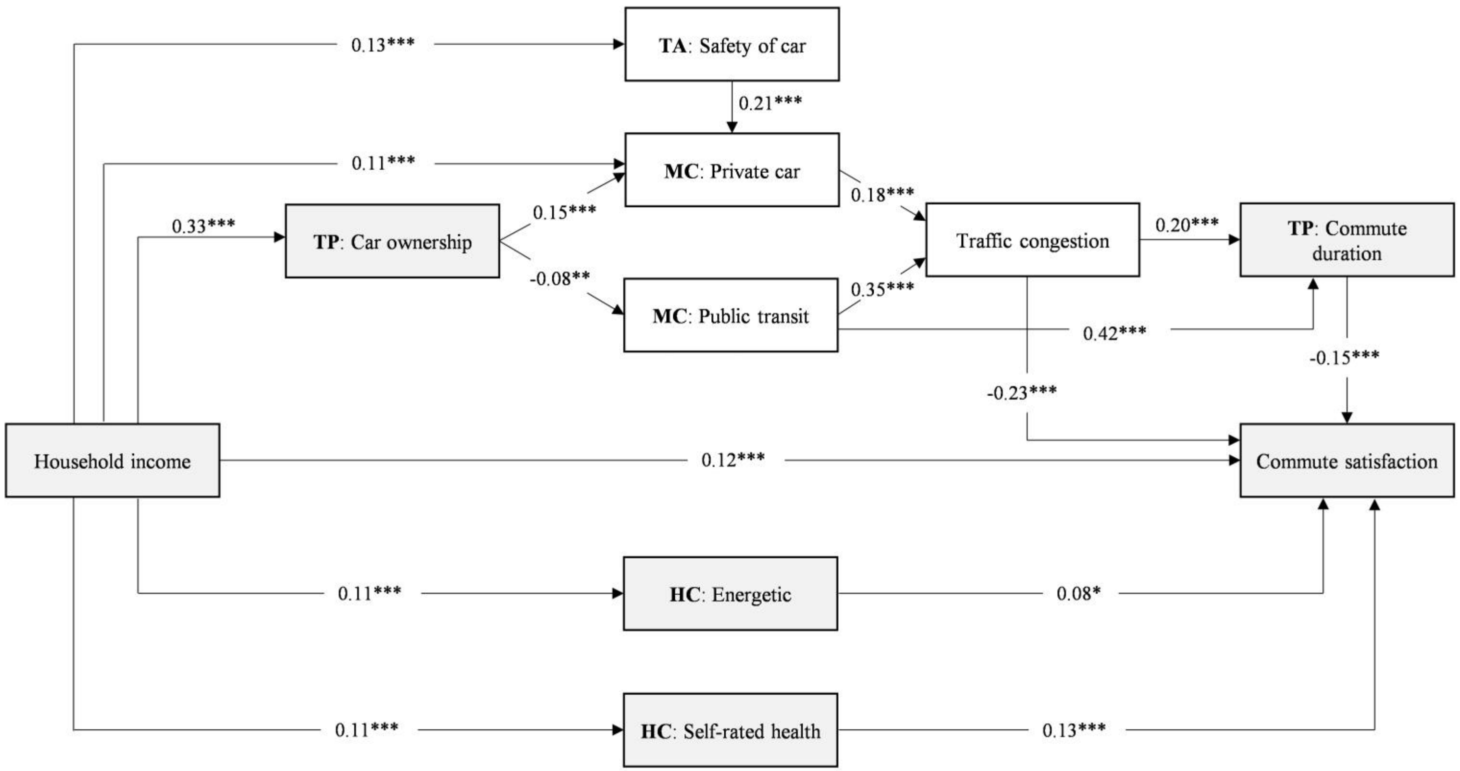
4 SEM results

This section discusses the SEM outcomes. For simplicity, only the direct paths from income levels to commute satisfaction and the indirect paths through transport poverty and health conditions are shown in Figures 5-8. Notably, 5% is commonly used by researchers as a cutoff *p*-value to determine the significance level. However, as discussed above, the sample size in the current study is sufficient but can hardly be considered sizeable for SEM analyses. In this case, it will be quite reasonable to relax the significance level from 5% to 10% (Stevens, 2009). Therefore, a cutoff *p*-value of 10% will be used to interpret the SEM results in the present study, which is a widely adopted criterion in transportation studies (e.g., Handy et al., 2005; Ma & Cao, 2019).

Amongst the four models, only one direct path from income levels to commute satisfaction is found. As Figure 5 shows, household income has a direct impact on satisfaction with commuting to work. Since this model controls for transport poverty and health conditions, it can be concluded that people from low-income households are less likely to be satisfied with commuting to work even if they have the same levels of transport poverty and health conditions as those from high-income households. In other words, the disparity in travel satisfaction across household income distributions cannot be mostly attributed to transport poverty and health conditions when commuting to work.

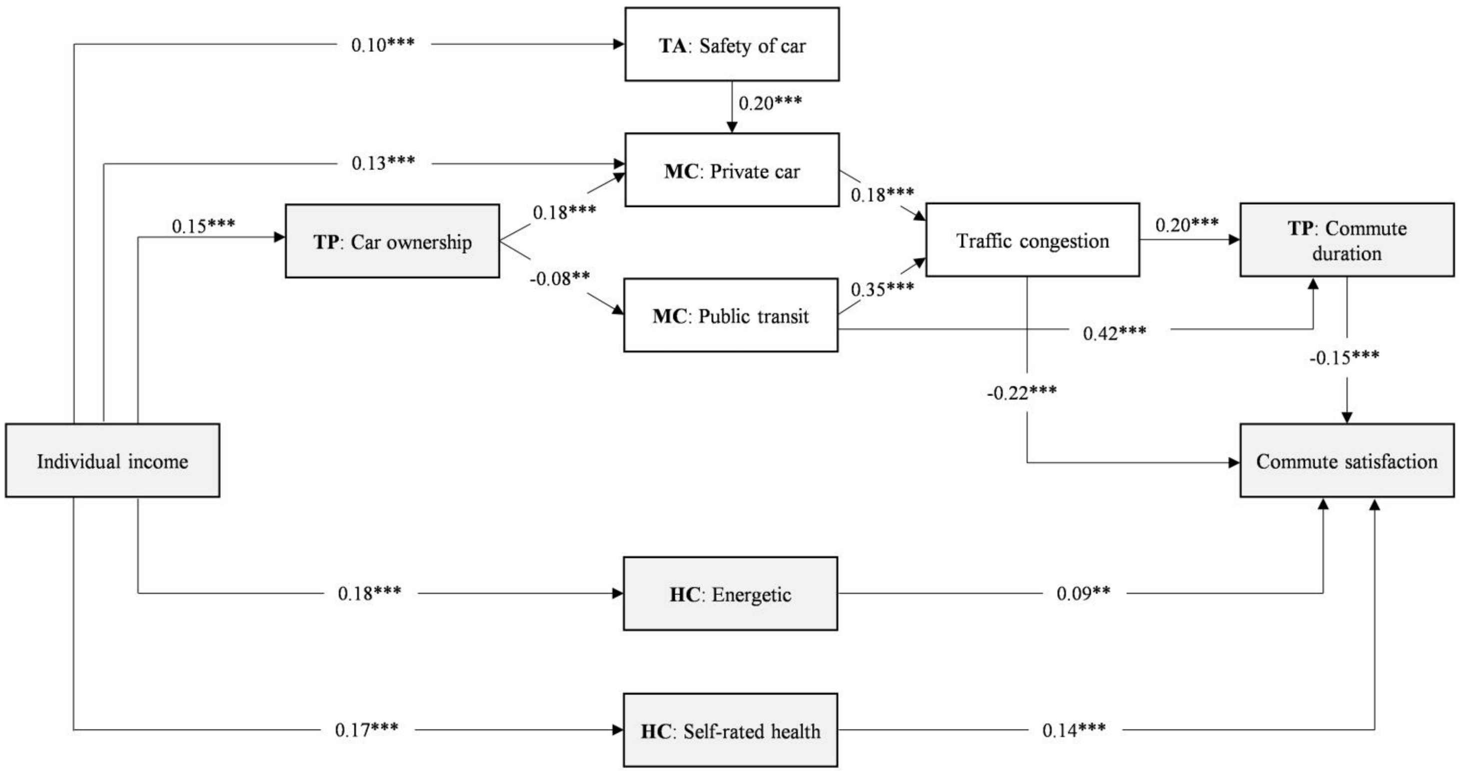
Four indirect paths from income levels to commute satisfaction are revealed in the four models. First, both household and individual incomes have indirect influences on the satisfaction with commuting to and from work through car ownership. The four models (see Figures 5-8) consistently show that people with high household and individual incomes are more likely to own private cars, which encourages them to more likely use cars for commuting but less likely use public transit. Meanwhile, compared to people using active modes, car users and public transit users are more likely to experience severe traffic congestions and long commute durations, which makes them feel less satisfied with commuting. This indirect path through car ownership indicates a complex relationship between income levels and commute satisfaction. On the one hand, low-income groups likely encounter transport poverty and feel less satisfied with commuting because they have limited access to cars and are "forced" to use public transit for commuting with high levels of traffic congestion and commute durations. On the other hand, although high-income groups have easy access to car use, the use of private cars for commuting also makes them experience severe traffic congestions and long commute durations, therefore leading to a low level of commute satisfaction as well.

Second, both household and individual incomes have indirect effects on satisfaction with commuting to and from work through travel attitudes and mode choice. As shown in Figures 5-8, high-income groups tend to be positive about the safety of cars and are more likely to use cars for commuting. As discussed above, however, the use of cars likely leads them to suffer from traffic congestion and spend more time commuting, resulting in low commute satisfaction.



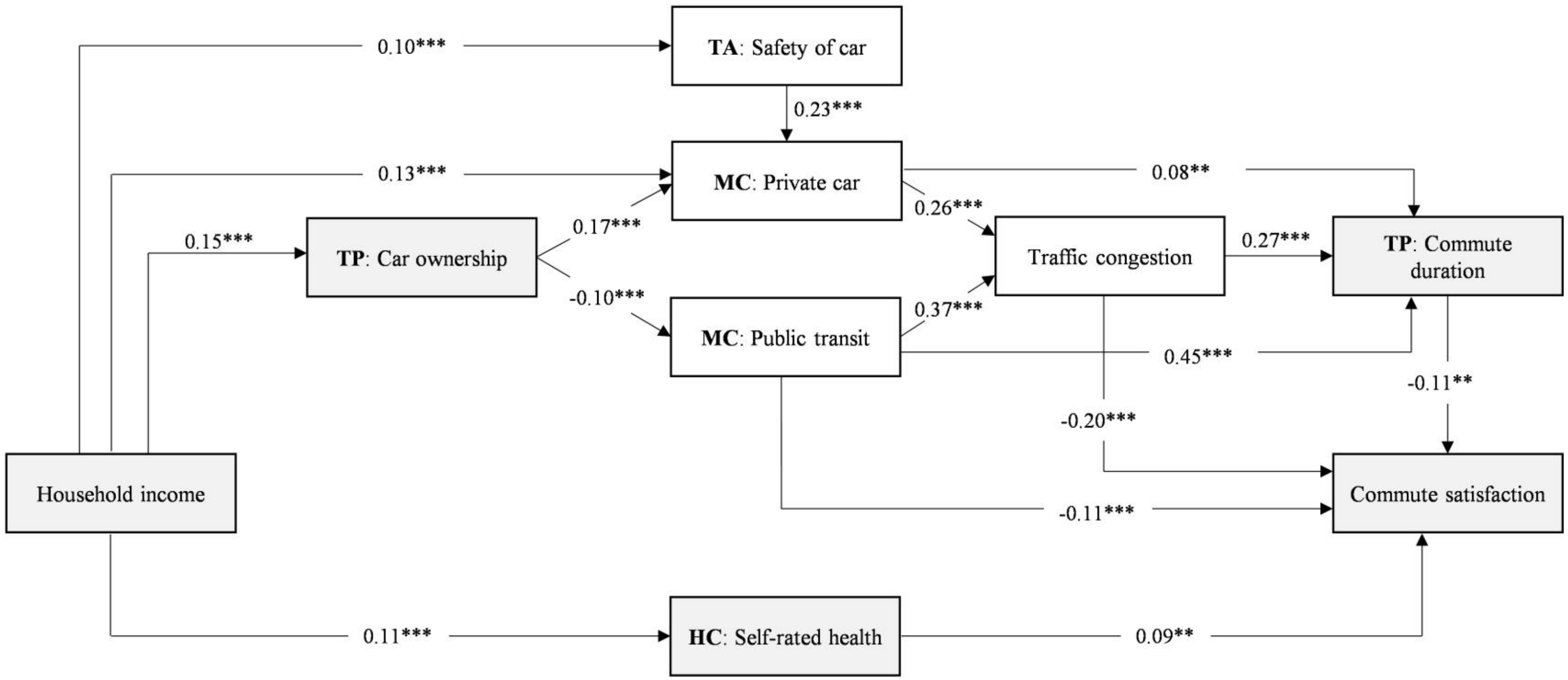
Note: "TP" represents "Transport Poverty"; "HC" represents "Health Condition"; "MC" represents "Mode Choice"; "TA" represents "Travel Attitude";
" * ", " ** ", and " *** " represent p<0.10, p<0.05, and p<0.01, respectively;
For the variable of mode choices, active modes (i.e., walking and cycling) are used as the reference category;
Model fit: CFI=0.96, RMSEA=0.031;
represents variables of interest.

Figure 5 SEM outcomes regarding the relationship between household income and the satisfaction with commuting to work (Standardized Coefficients)



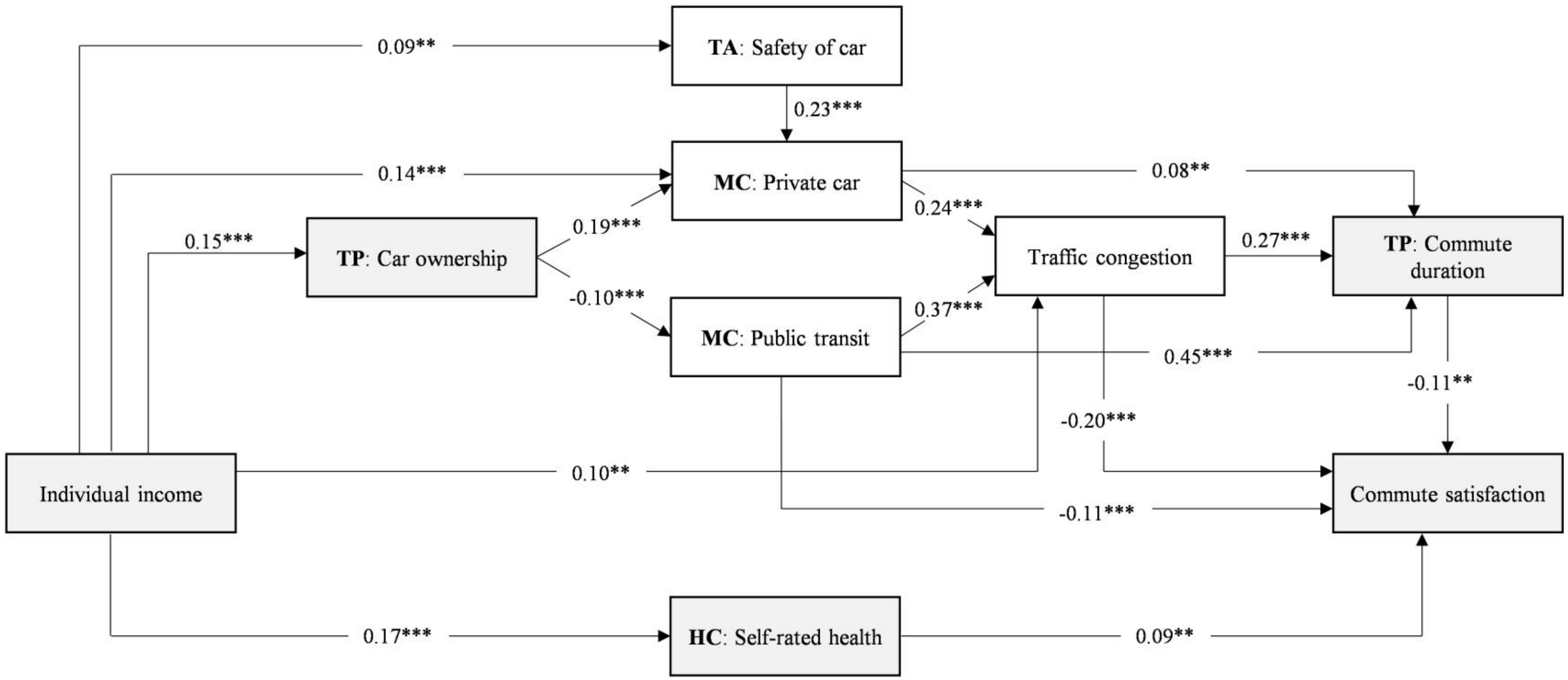
Note: "TP" represents "Transport Poverty"; "HC" represents "Health Condition"; "MC" represents "Mode Choice"; "TA" represents "Travel Attitude";
" * ", " ** ", and " *** " represent p<0.10, p<0.05, and p<0.01, respectively;
For the variable of mode choices, active modes (i.e., walking and cycling) are used as the reference category;
Model fit: CFI=0.96, RMSEA=0.031;
☐ represents variables of interest.

Figure 6 SEM outcomes regarding the relationship between individual income and the satisfaction with commuting to work (Standardized Coefficients)



Note: "TP" represents "Transport Poverty"; "HC" represents "Health Condition"; "MC" represents "Mode Choice"; "TA" represents "Travel Attitude";
" * ", " ** ", and " *** " represent p<0.10, p<0.05, and p<0.01, respectively;
For the variable of mode choices, active modes (i.e., walking and cycling) are used as the reference category;
Model fit: CFI=0.96, RMSEA=0.031;
☐ represents variables of interest.

Figure 7 SEM outcomes regarding the relationship between household income and the satisfaction with commuting from work (Standardized Coefficients)



Note: "TP" represents "Transport Poverty"; "HC" represents "Health Condition"; "MC" represents "Mode Choice"; "TA" represents "Travel Attitude";
" * " , " ** " , and " *** " represent p<0.10, p<0.05, and p<0.01, respectively;
For the variable of mode choices, active modes (i.e., walking and cycling) are used as the reference category;
Model fit: CFI=0.96, RMSEA=0.031;
☐ represents variables of interest.

Figure 8 SEM outcomes regarding the relationship between individual income and the satisfaction with commuting from work (Standardized Coefficients)

Third, both household and individual incomes indirectly influence satisfaction with commuting to and from work through health conditions. As presented in Figures 5-8, high income is positively associated with good health conditions, which is in line with our expectations. Meanwhile, people with a good health condition are more likely to indicate a high level of commute satisfaction.

Fourth, individual income indirectly impacts satisfaction with commuting from work through congestion. As Figure 8 displays, people with high individual incomes tend to report a high level of traffic congestion. A possible reason is that that affluent people care more about the consumption of time by their commutes and are more sensitive to traffic congestion. Consequently, they are likely to indicate long commute durations and feel unsatisfied with commuting.

5 Conclusions and discussion

In this study, we use data collected from a face-to-face survey performed in Chengdu (China) to investigate how commute satisfaction varies across income groups, and particularly examine the mediating roles of transport poverty and health conditions. SEMs are developed and reveal a complex mechanism behind how income influences commute satisfaction. On the one hand, low income makes people less satisfied with commuting in two ways. First, due to limited car ownership, low-income people tend to choose public transit for commuting. In this situation, they are more likely to encounter traffic congestion and long commute durations, leading to a low level of commute satisfaction. Second, low-income populations are inclined to have poor health conditions, which results in long commute duration and feel less satisfied with commuting. On the other hand, high incomes can also lead to a low level of commute satisfaction. High-income people tend to use private cars for commuting because of high availability of car use. Similarly, the use of private cars makes them more likely to experience severe congestion and long commute durations as well and consequently feel unsatisfied with commuting.

Another key objective of this study is to examine whether low-income people are likely to experience transport poverty and have poor health conditions. According to the SEM outcomes, people with low incomes tend to report low levels of health conditions. However, the relationship between income and transport poverty seems more complex. From the perspective of mobility poverty, it can be concluded that low-income people experience transport poverty because of their limited transport options (i.e., low level of car ownership). In terms of accessibility poverty, it can be inferred that both groups witness transport poverty since they both tend to have long commute durations. Therefore, the relationship between income and transport poverty depends on how transport poverty is defined. Two points need to be considered here. First, this paper only considers mobility poverty and accessibility poverty as the components of transport poverty. It is unknown how income is associated with transport poverty when taking transport unaffordability into consideration. Second, as Lucas (2012) pointed out, social consequences should be considered in the concept of transport poverty. This means that, for example, long commute durations (i.e., accessibility poverty) may not necessarily lead to time poverty (i.e., one aspect of social consequences) for people who have much spare time. Therefore, in the viewpoint of Lucas (2012), it is not fair to assert whether people witness transport poverty when social consequences are not considered.

Furthermore, as assumed before, low-income people may take two measures to reduce mobility poverty – they may buy a car, or they may reside or work in areas with high public transit accessibility. However, our findings show that low-income commuters do not choose to live or work in areas with more transit opportunities compared to high-income counterparts even though they have limited levels of car ownership. This means that low-income populations are not capable of reducing mobility poverty, which may be a result of high housing prices around transit stations in urban China (Tan et al., 2019; Yang et al., 2020).

According to the findings of the present study, some possible policy strategies can be recommended. Since commute satisfaction tends to be low not only for low-income groups but also – to a certain extent – for high-income groups, an inclusive urban transportation system may improve commute satisfaction of both. First, we find that both low- and high-income groups suffer from accessibility poverty because they often use non-active modes (i.e., cars and public transit) for commuting and consequently experience severe traffic congestion and long commute durations. From the perspective of urban planning, a possible practical solution is to improve walkability and optimize the safety and connectivity of cycling lanes to encourage the use of active modes (i.e., walking and cycling) for commuting. Second, we reveal that low-income people are less satisfied with commuting, mainly because of their poor health conditions. Therefore, improving health conditions may make positive contributions to their commute satisfaction. Some specific planning strategies like increasing public/open spaces and sport facilities, and improving access to healthy food, can be implemented in low-income communities to help them better manage their health conditions. In addition, encouraging the use of active modes will also be good for their health. However, the results also suggest a direct positive association between household income and satisfaction with commuting to work even if taking transport poverty and health conditions into account. This implies that taking actions only to reduce transport poverty and improve health conditions may not fully fill the commute satisfaction gap between various income groups, at least not in morning peak hours.

There are a few limitations in the present study. First, the lack of the profiles of the employment population across Chengdu city makes it difficult to assess the representativeness of the respondents used in this study. Nonetheless, it seems that young commuters are overrepresented to a certain extent, because only 8.6% of respondents are older than 40. This study aims to explore the relationships between potential explanatory factors and commute satisfaction rather than to predict commuting behavior per se. As such, the selection bias of respondents is not problematic (Babbie et al., 2007; Handy et al., 2005). Second, due to limited data availability, there exists a period gap of around one and a half years between the POI data on bus stations and the survey data. This may lead to some estimation errors. Third, the use of cross-sectional data in the current study tends to indicate correlations between variables rather than actual causality. A longitudinal design is often considered superior for causal inference and is therefore recommended for future research on this topic.

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Appendix A Pattern matrix of factor analysis for health conditions (N=608)

Factors	Questions	Loadings
Exhaustion	Have you felt tired recently?	0.91
	Have you felt worn out recently?	0.89
	Have you felt stressed recently in your everyday life?	0.48
Energetic	Have you felt full of pep recently?	0.92
	Have you had a lot of energy recently?	0.92
Self-rated health	How do you psychologically feel right now when thinking about your health?	0.91
	How do you physically feel right now when thinking about your health?	0.87

Appendix B Pattern matrix of factor analysis for travel attitudes (N=608)

Factors	Statements	Loadings
Pro-sustainable modes	I prefer to walk rather than drive whenever possible	0.73
	I prefer to take transit rather than drive whenever possible	0.73
	I prefer to ride a bicycle rather than drive whenever possible	0.70
	To me, walking is sometimes easier than driving	0.63
	To me, cycling is sometimes easier than driving	0.62
	To me, taking transit is sometimes easier than driving	0.59
	I like taking transit	0.54
	I like walking	0.44
Safety of car	Overall, driving is safer than walking	0.90
	Overall, driving is safer than taking transit	0.86
	Overall, driving is safer than cycling	0.75
Pro-car	I like driving	0.86
	I feel free and independent when I drive	0.83
	I like driving just for fun	0.79
Status of car	To me, driving is only a convenient way to get around	0.76
	To me, it does not matter which type of car I drive	0.65