Transportation (2021) 48:2357–2399
https://doi.org/10.1007/s11116-020-10133-9

# Do commuters adapt to in-vehicle crowding on trains?

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Published online: 28 July 2020


**Abstract**
In-vehicle crowding on public transportation is a serious problem that transportation planners must address. Recent studies have emphasized that in-vehicle crowding impacts travelers' stress and health, while other studies have investigated how daily travel affects subjective well-being (SWB). Based on the findings of these studies, we provide useful insights into the value of a reduction in crowding in terms of SWB. The other factor we should consider is adaptation, as the effects of travel discomfort disappear after travelers become accustomed to them. In this paper, we analyzed the direct and stress-related indirect effects of dissatisfaction with in-vehicle crowding on life satisfaction, focusing on whether these effects differ by the length of time commuters have been using trains. Using a sample of 8296 train commuters in Tokyo, we found that (1) dissatisfaction with in-vehicle crowding directly lowers life satisfaction among some groups of short-term train commuters and (2) dissatisfaction with in-vehicle crowding indirectly lowers life satisfaction through stress and health, regardless of whether commuters have used trains for more or less than one year. These results revealed the importance of focusing on the stress-related indirect effects of dissatisfaction with crowding, while direct effects on SWB exist only among some commuters. Our results demonstrated the possibility of adaptation to direct effects.

**Keywords** In-vehicle crowding · Stress and health · Experienced utility · Adaptation · Structural equation modeling

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## Introduction

Most urban areas suffer from serious traffic congestion that is attributable to high population density. Traffic congestion causes many problems, such as traveler stress and health effects (e.g., Cox et al. 2006; Currie and Walker 2011) and negative environmental externalities attributable to increased vehicle emissions (Zhang et al. 2011). Reducing congestion has great and obvious benefits. Policy makers and transportation planners need to know how much benefit will be gained from a costly project aimed at decreasing congestion. In the case of a public road, the benefit can be calculated by multiplying the reduced travel time by the value of time. Valuing in-vehicle crowding on public transport is somewhat dissimilar to the valuation for public road travel; the value is related to a comfort loss in the former but a time loss in the latter (Prud'homme et al. 2012).

Researchers have shown that in-vehicle crowding causes stress and health problems (Cox et al. 2006; Mohd Mahudin et al. 2011, 2012). In-vehicle crowding is also a determinant of waiting time, anxiety, exhaustion, safety, and choice of route and vehicle (Tirachini et al. 2013). Ignoring the effect of crowding causes an overestimation of demand for crowded public transport, which subsequently leads to overestimation of the benefits of travel in cost–benefit analysis (Batarce et al. 2016).

In-vehicle crowding on public transportation is also related to sustainable transportation policies. Although shifting to public transportation is repeatedly proposed as a solution to the environmental costs of mass automobile usage, this modal shift will lead to an increased level of crowding on public transportation, ultimately resulting in another welfare loss (Haywood et al. 2018). Several methods have been proposed to deal with crowding: increasing frequency, increasing the number of seats on public transit, increasing vehicle size, and imposing time-dependent fares (de Palma et al. 2017; Tirachini et al. 2013, 2014).

Previous studies have conducted stated preference (SP) surveys to investigate the value of in-vehicle crowding reduction on public transport (Basu and Hunt 2012; Batarce et al. 2016; Björklund and Swärdh 2017; Haywood and Koning 2015; Tirachini et al. 2017; Whelan and Crockett 2009). These studies required participants to select their preferred travel mode among hypothetical alternatives, which included attributes such as the level of crowdedness described by a picture showing the inside of the train/bus. The willingness to pay to reduce crowdedness was then calculated using coefficients in a utility function estimated by a choice model. Most of the studies focused on commuters: Batarce et al. (2016) included only workers, whereas Björklund and Swärdh (2017), Haywood and Koning (2015) and Whelan and Crockett (2009) included various types of users, although commuters occupied the largest share.

Some studies found that the value of crowding on public transport differs among individuals. Tirachini et al. (2017) showed that male, young and high-income travelers are sensitive to travel time but not to crowding compared with other types of travelers. In contrast, Haywood et al. (2017), who analyzed the effect of in-vehicle density on comfort satisfaction, showed that higher-income travelers are more sensitive to crowding.

Other studies have investigated in-vehicle crowding by revealed preference (RP) data. Hörcher et al. (2017), who used the RP method, suggested that SP studies overestimate the cost of in-vehicle crowding. Their study investigated travelers' route choice in public transport using automated fare collection data on travelers, including smart card data. Despite the attempt to simulate reality, there are a limited number of RP studies that have estimated in-vehicle crowding costs (Halvorsen et al. 2016; Tirachini et al. 2016). While the RP studies are superior in terms of controlling the real variability of in-vehicle conditions during a trip, the SP method still has the advantage of collecting target variables more easily even if the variable is unobservable in reality.

The Japanese government recommends using choice-based methods to investigate in-vehicle crowding. The Japanese guideline for railway project evaluations (MLIT 2012) recommends that transportation planners use a discrete choice model to calculate the value of crowding. Before they include in-vehicle crowding as an explanatory variable in the choice equation, they convert the crowding rate into a generalized time based on a formula suggested by MLIT (1999). Based on this method, Kato et al. (2003) calculated the benefit of easing in-vehicle crowding from a project related to the relocation of a station in the Tokyo area.

Although many studies and the Japanese government have explored travelers' mode choice behavior with SP and RP data to value in-vehicle crowding, evidence from recent studies implies that we should focus on the ex post evaluation of travel experiences because of the fundamental limitations of choice-based methods. The utility inferred from choice behavior is referred to as decision utility (Kahneman et al. 1997). The underlying assumption of the inference is that an individual predicts which travel mode is most likely to provide the highest utility among a set of alternatives. In other words, decision utility becomes a precise estimate of utility if an individual can accurately predict, at the time of mode choice, their future experiences of using transportation. However, previous studies have found that people are likely to underestimate the negative aspects of future commuting experiences and suffer more than they expected under the negative influences of travel (Frey and Stutzer 2014; Stutzer and Frey 2008). Although people can generally switch their commuting modes if they are dissatisfied with the current modes, such mode switching lacks feasibility if alternative modes to railway are not easily accessible. Despite the important roles that discrete choice methods play in demand prediction, the ex-ante choice model cannot precisely capture the stressful experience of crowding and its effects, especially for commuters living and working in an area with limited availability of alternative modes.

While SP and RP studies have focused on travelers' decision utility, other studies have analyzed travelers' experienced utility. Experienced utility refers to the experienced outcome of a choice (Ettema et al. 2010). One of the measures of experienced utility is the perceived quality of service (de Oña et al. 2013; dell'Olio et al. 2010). Some attributes such as comfort, safety, and space are recognized as determinants of the perceived quality of public transportation (de Oña and de Oña 2014). Furthermore, perceived quality of service has been found to determine travel satisfaction (Eboli and Mazzulla 2015). Subjective well-being (SWB) is another representative measure of experienced utility. Previous studies have analyzed the process of how daily travel affects life satisfaction, a frequently used proxy for SWB (Bergstad et al. 2011; Ettema et al. 2010; Friman et al. 2017).

Adaptation is a critical characteristic of experienced utility. Some researchers have found that a person's level of SWB has a specific reference point (e.g., Lucas 2007). A major life event, such as marriage or an increase in salary, has short-term effects on SWB but no long-lasting effect, which suggests that SWB returns to the reference point after some time. If we consider a change in the commuting mode as a life event, we can formulate a hypothesis that the effects of commuting discomfort might be different depending on how long of a period an individual has commuted by train. Although previous studies have found the negative effects of crowding on people's stress and health (Cox et al. 2006; Mohd Mahudin et al. 2012), whether adaptation can reduce the impact of in-vehicle crowding on stress and health remains an open question. Even if the direct effects on SWB do not exist, it is possible that the effects on people's health and stress subsist for commuters who used trains not only for the short term but also for the long term. There is little evidence for the existence of adaptation to train commuting.

In this study, we analyzed the effects of dissatisfaction with in-vehicle crowding on experienced utility using two-wave panel data. More specifically, we examined whether the effects of dissatisfaction with in-vehicle crowding on life satisfaction might differ by the length of time the commuters have been using the train. We hypothesized that the effects of dissatisfaction with crowding on life satisfaction are divided into two groups: direct effects and indirect effects (i.e., through stress and health).

We use a sample from Tokyo, where travelers frequently experience Japan's most severe in-vehicle crowding on trains. According to MLIT (2018), the average congestion rate of major railways in the greater Tokyo area during rush hour is 163%, which is higher than that in other major cities in Japan, such as the Chukyo area (around Nagoya) at 131% and the Keihanshin area (around Osaka) at 125%.[1] Commuters in Tokyo are experiencing the inconvenience of travel mode alternatives to trains due to the high parking rates and the poor bus route options. Thus, it is highly possible that the commuters tolerate train commuting even if they are dissatisfied with it, without switching to another mode.

The remainder of this paper is structured as follows. "Modeling framework" section describes the modeling framework built on previous studies, and "Data" section explains the data and the method used in the empirical analysis. "Results" section shows the results, and "Discussion" section discusses the results and concludes.

## Modeling framework

### Conceptual model

A structural model is specified in reference to two relationships identified by previous studies. One relationship concerns satisfaction with daily travel, emotional factors and SWB. Ettema et al. (2010) constructed a theoretical framework that describes how daily travel impacts SWB and hypothesized both direct and indirect effects of daily travel on SWB. Based on their framework, an empirical analysis was conducted, and evidence on the relationships was shown (Bergstad et al. 2011; De Vos 2019; De Vos and Witlox 2017; Friman et al. 2017). These studies suggest that satisfaction with travel attributes has both direct and indirect effects on SWB through affective, emotional factors.

The other relationship focuses on the influence of in-vehicle crowding in public transportation on stress and health. Cox et al. (2006) constructed a theoretical framework for how the passenger density of rail transport impacts stress and health by referring to extensive literature. They separated the meanings of density and crowding: density refers to an objective characteristic of an in-vehicle situation, whereas crowding stands for a subjective perception of the objective density. They then suggested that high passenger density is not necessarily recognized as a high level of crowding. Following this evidence, Mohd Mahudin et al. (2011, 2012) analyzed a model that specified the effects of passenger density and crowding and showed that affective reactions to crowding significantly predict commuter stress, which influences health, and feelings of exhaustion, which affect life satisfaction.

[1] Generally, the congestion rate is calculated by dividing the travel demand by the travel capacity. See Kidokoro (2006) for details.

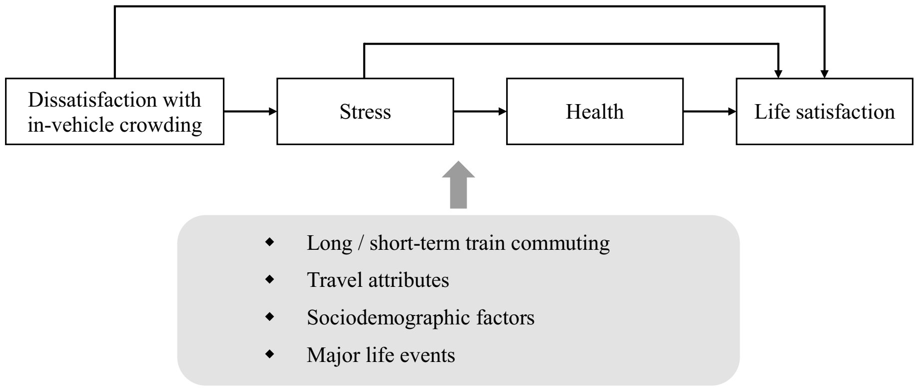


**Fig. 1** A hypothesized model outlining the relationships between stress, health, life satisfaction, and dissatisfaction with crowding

They also showed that passenger density does not influence either stress or feelings of exhaustion directly but does so indirectly through affective reactions to crowding. This evidence indicates that to evaluate a reduction in in-vehicle crowding, passengers' subjective evaluation of crowding should be a focus. The effects of crowding on stress are also found in neuroscientific studies. In an experiment, Kennedy et al. (2009) showed that close proximity to another person is found to activate one of the parts of the human brain related to stress reaction. In this experiment, the participants were facing each other. Although their study provides useful neuroscientific insights about stress and crowding, passengers are not always facing each other in reality. Taking this evidence into account, whether passenger density leads to crowding discomfort might be affected by whether passengers face each other.

Stress is known as a risk factor for health problems in the field of medical science. Mental stress is recognized as a major cause of cardiovascular disease (Greenwood et al. 1996). For instance, there is epidemiological evidence that perceived mental stress causes increased mortality from stroke and coronary heart disease (Iso et al. 2002). Furthermore, stress increases the risk of other diseases such as obesity (Torres and Nowson 2007), diabetes (Surwit et al. 2002), and asthma (Wright et al. 1998).

The two findings from these studies are key to constructing our model: (1) satisfaction with the travel conditions has direct and indirect effects on SWB through affective factors, and (2) passengers' affective reactions to in-vehicle crowding impact stress and health. Based on these findings, we construct a model outlining the relationships between in-vehicle crowding, stress, health and life satisfaction. The hypothesized model is shown in Fig. 1.

Endogenous variables in this model explain the major relations between the main components of our hypothesis: dissatisfaction with in-vehicle crowding has negative effects on life satisfaction both directly and indirectly via stress and health. We hypothesize the main relationships by combining the two findings from the frameworks mentioned above. On the basis of the finding about the relationship between satisfaction with travel and SWB, we use dissatisfaction with in-vehicle crowding as our main explanatory variable for satisfaction with travel. Because in-vehicle crowding may be perceived by commuters as having only negative aspects, we focus on dissatisfaction with crowding whereas previous studies have used satisfaction with overall travel. Then, on the basis of the finding related to crowding and stress, we include stress and health in our model as mediators between dissatisfaction with crowding and SWB. Finally, we use overall life satisfaction as a proxy for SWB; this measure is used more frequently than other measures, such as happiness and eudemonic well-being, in the context of travel behavior.

Exogenous variables play a role in controlling the variables used to refine the estimates of interest. Travel attributes influence satisfaction with travel (Friman et al. 2017), stress (Ettema et al. 2010; Evans and Wener 2006), health (Christian 2012), and life satisfaction (Frey and Stutzer 2014; Stutzer and Frey 2008). Sociodemographic factors such as age, gender and income have been found to affect various indicators in many studies on transportation, health and happiness; therefore, we assume that these factors affect all of the main variables.

Major life events are control variables that we also include in the modeling framework to avoid omitted variable bias. We should control events related to changes in the commuting mode, such as a move or job change, because they may be correlated with whether passengers are dissatisfied with in-vehicle crowding.

In addition, we hypothesize that the effects of dissatisfaction with crowding vary depending on whether individuals are accustomed to train commuting. As a proxy for the level of adaptation to train commuting, we focus on whether individuals are long-term or short-term train commuters. We also assume that the probability of being a long-term or short-term train commuter is determined by sociodemographic factors and life events.

## Estimation method

We use structural equation modeling (SEM) with observed variables (e.g. Bollen 1989) to estimate our hypothetical model and test differences depending on whether commuters are long-term train commuters.

We utilize the first-difference equation (e.g. Johnson 2005; Wooldridge 2010) to address the possibility of an endogeneity problem caused by time-invariant omitted variables. Whereas the first-difference equation is usually estimated by using OLS in many studies, some researchers have shown that the first-difference equation can also be estimated by the maximum likelihood method (Han and Phillips 2013; Kripfganz 2016). Differencing the regression equation across the two time periods can eliminate the time-invariant unobservable. This differencing procedure makes it possible to obtain the consistent estimated effects of independent variables if all omitted variables that might cause the endogeneity are constant over time. The time-varying error term needs to be uncorrelated with independent variables for all time periods, which is called the strict exogeneity of the independent variables.

The specification of our SEM model is shown in the following equations:

$$\begin{aligned}\Delta LS_i = \beta_{L,0} + \beta_{L,1}\Delta Crowding_i + \boldsymbol{\beta}'_{L,2}(\Delta Crowding_i \boldsymbol{Usertype}_i) + \boldsymbol{\beta}'_{L,3}\boldsymbol{Usertype}_i \\ + \beta_{L,4}\Delta Stress_i + \beta_{L,5}\Delta Health_i + \boldsymbol{\beta}'_{L,6}\boldsymbol{events_i} + \boldsymbol{\beta}'_{L,7}\Delta \boldsymbol{Control_i} + e_{L,i},\end{aligned} \tag{1}$$

$$\Delta Health_i = \beta_{H,0} + \beta_{H,1}\Delta Stress_i + \boldsymbol{\beta}'_{H,2}\boldsymbol{Usertype}_i + \boldsymbol{\beta}'_{H,3}\boldsymbol{events_i} + \boldsymbol{\beta}'_{H,4}\Delta \boldsymbol{Control_i} + e_{H,i}, \tag{2}$$

$$\Delta Stress_i = \beta_{S,0} + \beta_{S,1}\Delta Crowding_i + \boldsymbol{\beta}'_{S,2}(\Delta Crowding_i \boldsymbol{Usertype}_i) + \boldsymbol{\beta}'_{S,3}\boldsymbol{Usertype}_i + \boldsymbol{\beta}'_{S,4}\boldsymbol{events_i} + \boldsymbol{\beta}'_{S,5}\Delta\boldsymbol{Control_i} + e_{S,i}, \tag{3}$$

$$\Delta Crowding_i = \beta_{C,0} + \boldsymbol{\beta}'_{C,1}\boldsymbol{events_i} + \boldsymbol{\beta}'_{C,2}\Delta\boldsymbol{Control_i} + e_{C,i} \tag{4}$$

$$\boldsymbol{Usertype_i} = \begin{bmatrix} Bus_{15,i} \\ Car_{15,i} \\ MC_{15,i} \\ BC_{15,i} \\ FT_{15,i} \\ NC_{15,i} \\ Switched_i \end{bmatrix} = \begin{bmatrix} \beta_{Bus,0} \\ \beta_{Car,0} \\ \beta_{MC,0} \\ \beta_{BC,0} \\ \beta_{FT,0} \\ \beta_{NC,0} \\ \beta_{Switched,0} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\beta}'_{Bus,1} \\ \boldsymbol{\beta}'_{Car,1} \\ \boldsymbol{\beta}'_{MC,1} \\ \boldsymbol{\beta}'_{BC,1} \\ \boldsymbol{\beta}'_{FT,1} \\ \boldsymbol{\beta}'_{NC,1} \\ \boldsymbol{\beta}'_{Switched,1} \end{bmatrix} \boldsymbol{events}_i + \begin{bmatrix} \boldsymbol{\beta}'_{Bus,2} \\ \boldsymbol{\beta}'_{Car,2} \\ \boldsymbol{\beta}'_{MC,2} \\ \boldsymbol{\beta}'_{BC,2} \\ \boldsymbol{\beta}'_{FT,2} \\ \boldsymbol{\beta}'_{NC,2} \\ \boldsymbol{\beta}'_{Switched,2} \end{bmatrix} \boldsymbol{control_{15,i}} + \begin{bmatrix} e_{Bus,i} \\ e_{Car,i} \\ e_{MC,i} \\ e_{BC,i} \\ e_{FT,i} \\ e_{NC,i} \\ e_{Switched,i} \end{bmatrix}, \tag{5}$$

where $\Delta LS$, $\Delta Health$, $\Delta Stress$, and $\Delta Crowding$ are the changes in life satisfaction, health, stress, and dissatisfaction with in-vehicle crowding, respectively; $\boldsymbol{Control}$ is a vector of control variables; $i$ refers to the respondents; $L$, $H$, $S$, and $C$ are the initial letters of dependent variables in the equations; $\beta$ refers to an unknown parameter; and $e$ refers to an error term. A list of all of the explanatory variables and explained variables in our specification is shown in Table 8 in the "Appendix".

Equations (1)–(4) are first-difference equations in which the time-invariant unobserved effects have been eliminated. To obtain consistent estimators of the coefficients, the strict exogeneity of the independent variables must be satisfied. This means that if any independent variables are correlated with the time-varying unobserved factors for any time period, the consistency will be violated.

The reason we use the differencing equations is to address the potential issues of endogeneity and self-selection, both of which will violate the consistency of estimators. For example, there may be some omitted variables that affect both stress and dissatisfaction with crowding. There may also be unobserved factors such as travel attitudes that affect the probability of being a long/short-term train commuter, stress, health and life satisfaction. Assuming that both omitted factors and determinants of self-selection are time-invariant unobserved effects, a first-difference equation can eliminate such unobserved effects.[2]

[2] Before we performed the first-difference method, we preliminarily conducted a cross-sectional analysis by using 2016 data. This approach could not consistently estimate the effects of dissatisfaction with crowding if some omitted time-invariant variables such as travel attitudes affect both independent and dependent variables. To address this potential endogeneity, we eventually adopted the first-difference equation.

Following the method of setting up a first-difference equation, we include time-varying factors (e.g., commuting time and income) and dummy variables for the event occurring between the two time periods (e.g., a modal shift, job change, or move) and exclude time-invariant characteristics (e.g., gender and education year). We also exclude age as an independent variable in the first-difference equation because $\Delta Age$ with a 1-year change equals 1 among all respondents; then, the effect of age is contained in the y-intercepts.

We assume that the effects of $\Delta Crowding$ differ by user type because of adaptation. As shown in Eq. (5), ***Usertype*** is a vector of dummy variables. $Bus_{15}$ equals 1 if a respondent used the bus as his or her main commuting mode in 2015. Similarly, $Car_{15}$, $MC_{15}$, $BC_{15}$, $FT_{15}$, and $NC_{15}$ refer to car commuters, motorcycle (MC) commuters, bicycle (BC) commuters, on-foot (FT) commuters, and noncommuters (NC), respectively, in the previous year. We include the information about the previous commuting mode because a satisfaction rating is affected by a change compared with the reference point (Abou-Zeid et al. 2012). Our assumption is that commuters who start commuting by train feel a certain level of crowding differently depending on their reference points based on their previous commuting modes. In Eqs. (1) and (3), the interaction terms between $\Delta Crowding$ and ***Usertype*** are included. We recognize a respondent as a short-term train commuter if any one of these dummy variables equals 1. If a respondent's main commuting mode was the train in 2015, no dummy variable equals 1. Therefore, $\beta_{L,1}$ and $\beta_{S,1}$ refer to the effects of $\Delta Crowding$ for long-term train commuters, and $\boldsymbol{\beta}_{L,2}$ and $\boldsymbol{\beta}_{S,2}$ describe the differences in the effects between long-term and short-term train commuters.

We also include *Switched* in ***Usertype***, a dummy variable that equals 1 if a commuter commuted by train in 2015 but switched to another mode in 2016, to test whether a potential selection bias exists. There is a possibility that commuters with strong dissatisfaction with crowding have switched from train commuting to other modes. If this is the case, the short-term group may contain a larger proportion of highly dissatisfied users who have not yet switched to another mode than the long-term group, and this may be another reason for the difference in the effects of $\Delta Crowding$. To explore this possibility, we also estimate the difference in the effects of $\Delta Crowding$ between long-term train commuters and commuters who switched to another mode of transport. If the effects of $\Delta Crowding$ are more negative among the switched group than among the long-term group, being freed from the dissatisfaction with crowding will improve the switchers' life satisfaction, which implies that strong dissatisfaction with crowding is one of the reasons for switching to other modes.

The set of control variables, ***Control***, consists of commuting time and sociodemographic factors. We include the change in commuting time ($\Delta$*Commuting time*), a natural log of household income ($\Delta$ln(*Household income*)), and household size ($\Delta$*Household size*) as explanatory variables in Eqs. (1), (2), (3), and (4). We apply the logarithmic function of income, which is frequently adopted in studies of subjective evaluations of satisfaction and health (Jones and Wildman 2008; Stutzer 2004). In terms of Eq. (5), because ***Usertype*** is a set of dummy variables showing whether commuters shifted their major commuting mode between 2015 and 2016, age, gender, education year, household income in 2015, household size in 2015, and car ownership in 2015 are included as determinants of the modal shift. In contrast to Eqs. (1) through (4), household income is specified as linear in Eq. (5) because previous studies on modal choice typically adopted the linear function of income as an explanatory variable (e.g., Belgiawan et al. 2016; Clark et al. 2016; Ding et al. 2017). The set of dummy variables of life events that occurred between 2015 and 2016 (***events***) is included as explanatory variables in all the equations.

Maximum likelihood estimation, the most frequently used estimator, is applied. The maximum likelihood method in SEM can be performed under the assumption that all dependent and independent observed variables in the model follow a multivariate normal distribution.[3] In practical situations, the multivariate normality of data is often violated (Micceri 1989). However, the maximum likelihood approach is recommended because of its advantage in terms of robustness against violations of the multivariate normality assumption when the sample size is sufficiently large (Golob 2003; Satorra 1990).

## Data

We use two-wave panel data from a nationwide survey that we conducted over the Internet in Japan in 2015 and 2016. The sample was randomly collected from a research company's nationwide web panel. This survey investigated individuals' SWB and its determinants by asking a wide range of questions related to their socioeconomic characteristics, environmental preferences, transportation environment and commuting form.

We received 247,000 responses in 2015; among them, 131,000 individuals continued to participate in the 2016 survey. From this dataset, we extract 19,835 respondents who selected Tokyo as their prefecture of residence, representing 0.15% of all inhabitants in Tokyo. Among them, 14,187 respondents are workers.

From the sample of workers in Tokyo, we extract the respondents who used trains as a typical commuting mode. The respondents were asked, "Which transportation mode do you usually use when commuting?" and selected relevant responses from thirteen transportation modes. From the responses to this question, we identify train commuters who selected "train" as our target sample.

The aim of this study is to investigate the difference in the effects of dissatisfaction with in-vehicle crowding by how long the commuters have been using trains. We use the information about commuting modes in the previous year to identify accustomed and non-accustomed train commuters. Prior to performing the quantitative analysis, we categorized the respondents according to the following criteria:

(1) Commuters who used a train as a main commuting mode in 2015 and continued to commute by train in 2016;
(2) Commuters who used other forms of transportation as a main commuting mode in 2015 and switched to train commuting in 2016;
(3) Respondents who were not commuters in 2015 but started to commute by train in 2016;
(4) Commuters who used trains as a main commuting mode in 2015 and switched to other commuting modes in 2016 without changing their residence.

We identify the respondents who satisfy condition (1) as "long-term train commuters" (6971 observations) and the respondents who satisfy conditions (2) or (3) as "short-term train commuters" (1076 observations). We additionally derive the respondents who meet condition (4) and identify them as "commuters who switched from train to another mode" (249 observations) to test the existence of the selection problem that we mentioned in the previous section. Because the number of observations for analysis is insufficient, we exclude commuters who reported that their main commuting mode was the express bus,

[3] See Bollen (1989) or Satorra (1990) for details.

**Table 1** Representativeness of the sample of workers in Tokyo

| | Our survey | Government statistics |
|---|---|---|
| % Female | 29.1% | 34.9%[a] |
| Average commuting time (min) | 55.1 | 66.3[a] |
| Average age | 47.7 | 46.2[b] |
| Average household income (JPY/year) | 8.5 million | 7.3 million[b] |

[a]MLIT (2017)

[b]Workers in Tokyo prefecture instead of train commuters. MIC (2017); TMG (2016)

taxi, or another transportation mode from our analysis. In addition, the observations of the respondents who responded with "do not know" or "do not want to answer" regarding their income and/or education level are deleted. This leaves us with 8296 observations for our analysis.

Table 1 shows the average age, percentage of females, average commuting time and average household income in both our survey and government statistics to assess the sample representativeness of our survey. In our survey, male commuters are slightly overrepresented compared to their proportion in the worker population in Tokyo.

Table 2 shows the characteristics of the sample and the percentages of the categories or mean values of the variables reported by the respondents that we include in our analytical model. The rightmost column shows the statistical significance of the difference in the means ($t$ test) or proportions ($z$ test) between the long-term group and the other two groups.

*Dissatisfaction with in-vehicle crowding* The respondents were asked, "Please select all items that you are dissatisfied with about transportation in your living environment." We identify the respondents who selected "crowding inside of public transportation" as train commuters who are dissatisfied with in-vehicle crowding. The percentage of dissatisfied commuters is significantly higher among the long-term group than among the short-term and switched groups, which means that the long-term train commuters are more likely to be dissatisfied with in-vehicle crowding than the other groups.

*Stress and health* The respondents also reported the frequency of feeling a high level of stress and a low level of stress on a 5-point scale: 1 "hardly ever" to 5 "very often". We average the frequencies of high and low levels of stress and include them as a stress variable in the analytical model. In addition, we derive the level of the respondents' health from their answers to the question "All in all, how would you describe your state of health?" on a 5-point scale from 1 "very poor" to 5 "very good". No significant differences in the means of these variables were observed among the groups.

*Life satisfaction* We use the indicator of life satisfaction as a response variable. Life satisfaction is based on the question, "Overall, how satisfied are you with your life?" The responses range on a scale from 1 "completely dissatisfied" to 5 "completely satisfied". The mean value of life satisfaction for the switched group is significantly lower than that for the long-term group.

We use three types of control variables: travel attributes, sociodemographic factors and major life events from the previous year.

*Travel attributes* We use respondents' commuting time as one of the variables for travel attributes in Eqs. (1) through (4). The respondents reported their usual one-way commuting time in increments of ten minutes. The average commuting time is lower among commuters who switched from trains to other modes than among the long-term group. The short-term

**Table 2** Characteristics of the three groups of train commuters

| | Long-term train commuters | Short-term train commuters | Switched to another mode | Pooled | Test for difference | |
|---|---|---|---|---|---|---|
| | | | | | Short vs. Long[c] | Switched vs. Long[c] |
| Sample size | 6971 | 1076 | 249 | 8,296[a] | | |
| Main commuting mode in 2015 | | | | | | |
| Train | 6971 | | 249 | 7220 | | |
| Bus | | 123 | | 123 | | |
| Car | | 159 | | 159 | | |
| Motorcycle | | 34 | | 34 | | |
| Bicycle | | 268 | | 268 | | |
| On foot | | 260 | | 260 | | |
| Non-commuter | | 232 | | 232 | | |
| Low level of stress | | | | | | |
| Hardly ever (1) | 2.6% | 2.7% | 3.2% | 2.6% | | |
| Not very often (2) | 10.1% | 10.0% | 10.0% | 10.1% | | |
| Neither (3) | 22.4% | 21.3% | 25.3% | 22.3% | | |
| Some of the time (4) | 44.9% | 46.6% | 41.8% | 45.0% | | |
| Very often (5) | 20.0% | 19.4% | 19.7% | 20.0% | | |
| M/SD | 3.7/1.0 | 3.7/1.0 | 3.6/1.0 | 3.7/1.0 | 0.0 | −0.8 |
| High level of stress | | | | | | |
| Hardly ever (1) | 6.8% | 6.8% | 4.8% | 6.8% | | |
| Not very often (2) | 23.0% | 21.4% | 20.1% | 22.7% | | |
| Neither (3) | 26.2% | 24.9% | 30.1% | 26.1% | | |
| Some of the time (4) | 31.5% | 33.8% | 32.9% | 31.9% | | |
| Very often (5) | 12.4% | 13.2% | 12.1% | 12.5% | | |
| M/SD | 3.2/1.1 | 3.3/1.1 | 3.3/1.1 | 3.2/1.1 | 1.6 | 1.1 |
| Self-reported health | | | | | | |

**Table 2** (continued)

| | Long-term train commuters | Short-term train commuters | Switched to another mode | Pooled | Test for difference | |
|---|---|---|---|---|---|---|
| | | | | | Short vs. Long[c] | Switched vs. Long[c] |
| Very poor (1) | 2.8% | 4.1% | 3.2% | 3.0% | | |
| Poor (2) | 16.2% | 17.4% | 14.1% | 16.3% | | |
| Neither (3) | 29.5% | 27.0% | 30.5% | 29.2% | | |
| Good (4) | 37.4% | 36.2% | 39.8% | 37.3% | | |
| Very good (5) | 14.1% | 15.3% | 12.5% | 14.2% | | |
| M/SD | 3.4/1.0 | 3.4/1.1 | 3.4/1.0 | 3.4/1.0 | −0.7 | 0.0 |
| Life satisfaction | | | | | | |
| Completely dissatisfied (1) | 5.0% | 5.7% | 6.4% | 5.1% | | |
| Slightly dissatisfied (2) | 12.6% | 15.4% | 15.3% | 13.0% | | |
| Neither (3) | 19.8% | 18.4% | 23.3% | 19.7% | | |
| Slightly satisfied (4) | 56.5% | 52.7% | 46.2% | 55.7% | | |
| Completely satisfied (5) | 6.1% | 7.9% | 8.8% | 6.5% | | |
| M/SD | 3.5/1.0 | 3.4/1.0 | 3.4/1.0 | 3.5/1.0 | −1.4 | −1.7* |
| % Dissatisfied with in-vehicle crowding | 28.1% | 24.8% | 14.5% | 27.3% | −2.3** | −4.7*** |
| Travel attributes | | | | | | |
| Average commuting time (min) (M/SD) | 56.5/31.8 | 50.1/44.6 | 36.9/57.7 | 55.1/34.9 | −5.8*** | −9.2*** |
| Average nominal commuting cost (JPY/day) (M/SD) | 990.1/2576.1 | 1009.0/3956.6 | 556.2/1784.3 | 979.5/2776.0 | 0.2 | −2.6*** |
| Average commuting cost adjusted by commuting allowance (JPY/day) (M/SD) | 94.3/857.0 | 172.9/1179.8 | 74.9/343.1 | 103.9/895.5 | 2.6*** | −0.4 |
| Sociodemographic characteristics | | | | | | |
| Average age (M/SD) | 47.7/9.5 | 47.4/10.5 | 47.6/11.0 | 47.7/9.7 | −1.0 | −0.3 |
| % Female | 28.0% | 35.3% | 30.9% | 29.1% | 4.9*** | 1.0 |
| Education level | | | | | | |
| Junior high school or less | 0.8% | 1.5% | 3.2% | 1.0% | | |

**Table 2** (continued)

| | Long-term train commuters | Short-term train commuters | Switched to another mode | Pooled | Test for difference | |
|---|---|---|---|---|---|---|
| | | | | | Short vs. Long[c] | Switched vs. Long[c] |
| High school | 12.7% | 17.0% | 19.3% | 13.5% | | |
| Some college | 15.3% | 19.5% | 18.9% | 16.0% | | |
| Bachelor's degree | 60.7% | 52.3% | 52.6% | 59.4% | | |
| Master's degree | 8.7% | 6.7% | 4.8% | 8.3% | | |
| Doctor's degree | 1.7% | 3.1% | 1.2% | 1.9% | | |
| Average education year (M/SD) | 15.4/2.0 | 15.1/2.2 | 14.7/2.3 | 15.3/2.1 | −3.9*** | −4.6*** |
| *Annual household income* | | | | | | |
| $<2$ million JPY[b] | 2.9% | 7.6% | 6.8% | 3.7% | | |
| 2–3 million JPY | 5.8% | 7.8% | 13.3% | 6.3% | | |
| 3–4 million JPY | 7.9% | 11.4% | 8.8% | 8.4% | | |
| 4–5 million JPY | 9.4% | 9.7% | 14.5% | 9.6% | | |
| 5–6 million JPY | 9.6% | 9.8% | 10.0% | 9.6% | | |
| 6–7 million JPY | 9.3% | 8.7% | 8.0% | 9.2% | | |
| 7–8 million JPY | 8.8% | 8.5% | 3.2% | 8.6% | | |
| 8–9 million JPY | 8.6% | 6.8% | 6.8% | 8.3% | | |
| 9–10 million JPY | 9.0% | 6.7% | 7.2% | 8.6% | | |
| 10–15 million JPY | 20.0% | 15.0% | 12.1% | 19.1% | | |
| 15–20 million JPY | 5.7% | 4.2% | 4.4% | 5.5% | | |
| 20–30 million JPY | 2.2% | 2.2% | 3.2% | 2.2% | | |
| $\geq 30$ million JPY | 0.9% | 1.6% | 1.6% | 1.0% | | |
| M/SD | 8.6/5.4 | 7.8/5.9 | 7.6/6.3 | 8.5/5.5 | −4.6*** | −2.9*** |
| Average household size (person) (M/SD) | 2.5/1.3 | 2.5/1.3 | 2.3/1.3 | 2.5/1.3 | −0.2 | −2.6*** |
| % Attitude to crowding | 12.8% | 13.2% | 10.8% | 12.8% | 0.4 | −0.9 |
| Car ownership in household | | | | | | |

**Table 2** (continued)

| | Long-term train commuters | Short-term train commuters | Switched to another mode | Pooled | Test for difference | |
|---|---|---|---|---|---|---|
| | | | | | Short vs. Long[c] | Switched vs. Long[c] |
| 0 | 52.1% | 48.7% | 56.2% | 51.7% | | |
| 1 | 44.3% | 44.5% | 39.8% | 44.2% | | |
| 2 | 3.3% | 5.9% | 2.8% | 3.6% | | |
| 3 | 0.3% | 0.8% | 1.2% | 0.4% | | |
| 4 | 0.0% | 0.2% | 0.0% | 0.1% | | |
| 5 or more | 0.1% | 0.0% | 0.0% | 0.1% | | |
| M/SD | 0.5/0.6 | 0.6/0.7 | 0.5/0.6 | 0.5/0.6 | 3.7*** | −0.8 |
| Major life events within 1 year | | | | | | |
| % Starting work | 0.6% | 1.7% | 2.0% | 0.8% | 3.6*** | 2.5** |
| % Restarting work | 1.7% | 6.4% | 6.4% | 2.4% | 9.6*** | 5.5*** |
| % Job-change | 4.7% | 9.6% | 12.9% | 5.6% | 6.5*** | 5.8*** |
| % Promotion | 3.3% | 3.3% | 2.8% | 3.2% | 0.0 | −0.4 |
| % Moving | 5.6% | 9.8% | 0.0% | 6.0% | 5.3*** | −3.8*** |
| % Marriage | 1.3% | 1.9% | 1.6% | 1.4% | 1.4 | 0.4 |
| % Divorce | 0.5% | 0.8% | 1.2% | 0.5% | 1.6 | 1.7* |
| % Birth of child | 1.7% | 1.8% | 0.8% | 1.7% | 0.2 | −1.1 |
| % Traffic accident | 1.1% | 2.6% | 1.6% | 1.3% | 3.9*** | 0.8 |
| % Death within family | 3.8% | 5.1% | 2.4% | 3.9% | 2.0** | −1.1 |
| % Purchase of house | 1.0% | 1.4% | 0.8% | 1.0% | 1.3 | −0.3 |
| % Purchase of condominium | 1.3% | 1.4% | 0.4% | 1.3% | 0.2 | −1.3 |

[a]Sums

[b]JPY (Japanese Yen) approximately equal to USD 0.009

[c]t-test for the difference between two means and $z$ test for the difference in proportions

*$p<0.1$; **$p<0.05$; ***$p<0.01$

group also has a lower average commuting time than the long-term group. Respondents also reported their commuting cost and commuting allowance. We calculate the net commuting cost by subtracting the amount of reported commuting allowance from the amount of reported commuting cost. Nominal and net commuting costs are shown only to describe the sample characteristics and were not included in our analytical model because this variable is available only for data from the 2016 survey. While the average nominal cost for the switched group is lower than that for the long-term group, the average net cost is higher among the short-term group than among the long-term group. The potential reason for this difference is that commuting allowance may be lower or there may be more workers who do not receive a commuting allowance in the short-term group.

*Sociodemographic and attitudinal factors* We include household income and household size as control variables in Eqs. (1) through (5). In addition to these variables, age, gender, education year, car ownership, and attitude toward crowding are included in Eq. (5). Attitude toward crowding is a dummy variable that equals 1 if a respondent checked the item, "I want to avoid crowding and congestion even if I spend money and time to do so".

*Major life events from last year* The respondents reported major life events that had occurred within the past year. We then use 12 dummy variables to indicate whether the respondents had experienced each life event within the one-year period. In particular, work-related life events are controlled because these factors may be correlated with whether respondents are long-term train commuters. Divorce, traffic accidents and a death in the family may be triggers of other events, such as a job change or modal shift. Purchasing a new house or a condominium may also be correlated with the change in commuting time.

The percentage of female commuters is higher among the short-term group than among the other groups. In addition, the short-term and switched groups have a lower average education year and lower average household income than the long-term group. These characteristics may be explained by some sociodemographic trends. In Japan, the proportion of permanent regular workers is lower for female workers than for male workers (Kawaguchi and Ueno 2013). The group of nonpermanent workers also has a high proportion of individuals with lower years of education (Honda 2004). Additionally, nonpermanent workers might be more likely than permanent workers to switch their commuting mode frequently because of a job change. The correlations among these factors may be the determinants of the differences in sociodemographic variables among the groups.

Table 3 summarizes the changes in the variables. For the long-term group, the change in dissatisfaction with crowding might have been caused by a change in the level of crowding for some reason, such as a change in commuting hours (from or to rush hour). For the short-term and switched groups, the major reason for the change in dissatisfaction with crowding appears to have been the change in the commuting mode. Moreover, the summary shows that commuting time increased for the group of commuters who began train commuting, while commuting time decreased for the group who quit train commuting. In terms of the other variables, there were no substantial differences among the groups. In our estimation, we average the change in high and low stress levels and used them as an explanatory variable.

**Table 3** Summary of changes in the variables

| | Long-term train commuters | Short-term train commuters | Switched to another mode | Pooled |
|---|---|---|---|---|
| ΔCrowding | | | | |
| − 1 | 8.7% | 6.2% | 10.0% | 8.5% |
| 0 | 73.9% | 76.6% | 79.5% | 74.4% |
| 1 | 17.4% | 17.2% | 10.4% | 17.2% |
| M/SD | 0.087/0.50 | 0.11/0.47 | 0.0040/0.45 | 0.087/0.50 |
| ΔLow stress | | | | |
| − 4 | 0.3% | 0.3% | 0.8% | 0.3% |
| − 3 | 1.0% | 1.2% | 1.2% | 1.1% |
| − 2 | 5.9% | 5.2% | 6.8% | 5.9% |
| − 1 | 20.3% | 21.1% | 19.7% | 20.4% |
| 0 | 46.5% | 45.5% | 50.6% | 46.5% |
| 1 | 18.4% | 17.8% | 12.1% | 18.1% |
| 2 | 6.0% | 7.1% | 7.6% | 6.2% |
| 3 | 1.3% | 1.7% | 0.8% | 1.3% |
| 4 | 0.2% | 0.2% | 0.4% | 0.2% |
| M/SD | − 0.011/1.1 | 0.015/1.1 | − 0.088/1.1 | − 0.0098/1.1 |
| ΔHigh stress | | | | |
| − 4 | 0.1% | 0.2% | 0.0% | 0.1% |
| − 3 | 1.2% | 1.3% | 1.6% | 1.2% |
| − 2 | 7.1% | 8.1% | 8.0% | 7.3% |
| − 1 | 22.3% | 19.3% | 20.9% | 21.8% |
| 0 | 46.0% | 45.9% | 44.6% | 46.0% |
| 1 | 17.1% | 17.6% | 17.3% | 17.2% |
| 2 | 5.1% | 6.7% | 6.0% | 5.3% |
| 3 | 0.9% | 0.7% | 1.6% | 0.9% |
| 4 | 0.2% | 0.2% | 0.0% | 0.2% |
| M/SD | − 0.098/1.1 | − 0.062/1.1 | − 0.076/1.1 | − 0.093/1.1 |
| ΔHealth | | | | |
| − 4 | 0.1% | 0.3% | 0.0% | 0.1% |
| − 3 | 0.6% | 0.8% | 0.0% | 0.6% |
| − 2 | 4.1% | 4.7% | 3.2% | 4.2% |
| − 1 | 20.3% | 20.2% | 24.1% | 20.4% |
| 0 | 56.6% | 55.7% | 52.6% | 56.3% |
| 1 | 15.2% | 13.9% | 18.1% | 15.1% |
| 2 | 2.8% | 3.9% | 2.0% | 2.9% |
| 3 | 0.3% | 0.4% | 0.0% | 0.3% |
| 4 | 0.0% | 0.2% | 0.0% | 0.1% |
| M/SD | − 0.088/0.85 | − 0.095/0.93 | − 0.084/0.79 | − 0.089/0.86 |
| ΔLife satisfaction | | | | |
| − 4 | 0.0% | 0.0% | 0.0% | 0.0% |
| − 3 | 0.4% | 0.5% | 0.4% | 0.4% |
| − 2 | 2.7% | 3.7% | 5.6% | 2.9% |
| − 1 | 14.7% | 14.3% | 18.1% | 14.7% |
| 0 | 62.6% | 60.3% | 54.6% | 62.1% |

**Table 3** (continued)

| | Long-term train commuters | Short-term train commuters | Switched to another mode | Pooled |
|---|---|---|---|---|
| 1 | 15.6% | 15.2% | 17.3% | 15.6% |
| 2 | 3.3% | 4.7% | 2.8% | 3.5% |
| 3 | 0.5% | 0.8% | 1.2% | 0.6% |
| 4 | 0.1% | 0.5% | 0.0% | 0.1% |
| M/SD | 0.026/0.80 | 0.058/0.90 | −0.040/0.91 | 0.028/0.82 |
| ΔCommuting time (min) (M/SD) | 2.9/29.9 | 21.9/48.2 | −10.5/58.6 | 5.0/34.7 |
| Δln(Household income) (M/SD) | −0.012/0.34 | −0.033/0.45 | −0.096/0.48 | −0.018/0.36 |
| ΔHousehold size (M/SD) | 0.014/0.56 | 0.033/0.72 | −0.028/0.56 | 0.015/0.58 |

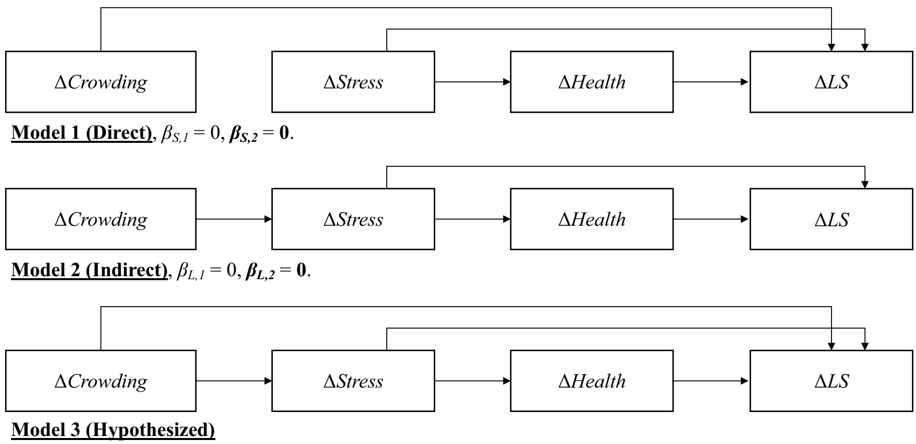


**Fig. 2** Suggested models for comparison (only related variables and paths are shown)

## Results

### Overall tendency of direct and indirect effects

First, we investigate the overall significance of the direct and indirect effects of dissatisfaction with crowding without consideration of the user types. We compared the three suggested models shown in Fig. 2 to test whether including the set of direct effects and the set of indirect effects will significantly improve the model fit. Model 1 includes only direct effects, Model 2 includes only indirect effects through stress and health, and Model 3 includes both direct and indirect effects. We used the following goodness-of-fit indices, which have been frequently used in previous studies: the Chi square over degrees of freedom, the standardized root mean residual (SRMR), the comparative fit index (CFI), the root mean square error of approximation (RMSEA) and Akaike's information criterion (AIC). Next, we interpreted the coefficient estimates and compared the estimated effect between long-term and short-term train commuters. Finally, we calculated the indirect effects of dissatisfaction with crowding from the direct effects.

**Table 4** Goodness-of-fit indices of the suggested models

| Model | $\chi^2$ (df) | $\chi^2$/df (< 5) | SRMR (< .05) | CFI (≥ .95: good) (> .90: acceptable) | RMSEA (< .08) | AIC (lowest) | LR test (vs. Hypothesized) $\chi^2$ (df) |
|---|---|---|---|---|---|---|---|
| 1 (Direct) | 720.763*** (156) | 4.620 | 0.010 | 0.900 | 0.021 | 113,493.264 | 20.19*** (8) |
| 2 (Indirect) | 713.104*** (156) | 4.571 | 0.010 | 0.901 | 0.021 | 113,485.605 | 12.53 (8) |
| 3 (Hypothesized) | 700.578*** (148) | 4.734 | 0.010 | 0.902 | 0.021 | 113,489.079 | – |

***$p < 0.01$

According to the values of the goodness-of-fit indices, in general, the models fit the data well. Table 4 shows the most frequently used fit indices for each model and a cutoff value for each index (see, for instance, Brown 2006; Mohd Mahudin et al. 2012; Ye and Titheridge 2017). Significant Chi squares were observed for all of the posited models. Because these indices are influenced by the large sample size (n = 8296), we looked at other fit indices that can take a large sample size into account. SRMR, CFI, and RMSEA showed that the models were acceptable.

We showed that Model 3 fit significantly better than Model 1 according to the likelihood-ratio (LR) tests. We conducted LR tests because the differences in the values of goodness of fit were too trivial to decide which model was the most suitable. The rightmost column of Table 3 shows the results of the LR tests of Model 1 and Model 2 compared to Model 3. Model 3 was not significantly different from Model 2 in terms of goodness of fit, which implies that there were no overall direct effects of dissatisfaction with crowding. However, this procedure cannot clarify the difference in the significance of the direct effects by the user types in detail. To take the possible difference into account, we adopt Model 3 to perform the estimation considering differences among the groups in detail. The estimation results of Model 3 are described in the next subsection. The results of Models 1 and 2 are shown in Tables 9 and 10 in the "Appendix".

## Model estimation

The results of the hypothesized model estimation, including standardized coefficients and significance, are shown in Table 5. Standardized coefficients are used to make the interpretation of the estimated effects comparable between independent variables (e.g., You 2017). Standardized coefficients describe the change in a dependent variable when an independent variable increases by a standard deviation. Therefore, the coefficients can be interpreted as the relative importance of different independent variables.

Regardless of whether the respondents were long-term or short-term train commuters, there was a significant relationship between crowding and life satisfaction mediated by stress and health (1st to 10th rows of Table 5). Stress was significantly predicted by crowding and significantly predicted health. These results suggest that dissatisfaction with in-vehicle crowding is associated with a higher frequency of stress and that a higher frequency of stress induces a lower level of health. In addition, both stress and health have significant effects on life satisfaction; a high frequency of stress significantly lowers life satisfaction, and a high level of health significantly increases life satisfaction. Because none of the interaction terms between $\Delta Crowding$ and the dummy variables of short-term train commuters were significant, there was no difference in the effect of dissatisfaction with crowding on stress between long-term and short-term train commuters. Similarly, there was no significant difference in the stress-related effects between long-term train commuters and commuters who switched from a train to other travel modes.

We found a difference in the direct effects of dissatisfaction with crowding on life satisfaction depending on whether respondents were long-term or short-term train commuters (1st to 8th rows of Table 5). The significance levels of $\Delta Crowding$ and the interaction terms indicate that dissatisfaction with in-vehicle crowding induced a lower level of life satisfaction among short-term train commuters who originally commuted by taking a bus, driving a car or walking in the previous year, whereas this was not the case among long-term train commuters; crowding did not have significant effects on life satisfaction for those who commuted by train for a longer period. Dissatisfaction with crowding had no

**Table 5** Standardized coefficient estimates of the hypothesized model

| | ΔCrowding | ΔStress | ΔHealth | ΔLS | Short-term ($Bus_{15}$) | Short-term ($Car_{15}$) | Short-term ($MC_{15}$) | Short-term ($BC_{15}$) | Short-term ($FT_{15}$) | Short-term ($NC_{15}$) | Switched |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Main variables | | | | | | | | | | | |
| 1. ΔCrowding | | 0.039*** | | 0.006 | | | | | | | |
| 2. ΔCrowding × Short-term ($Bus_{15}$) | | 0.008 | | −0.019* | | | | | | | |
| 3. ΔCrowding × Short-term ($Car_{15}$) | | 0.002 | | −0.024** | | | | | | | |
| 4. ΔCrowding × Short-term ($MC_{15}$) | | −0.007 | | −0.010 | | | | | | | |
| 5. ΔCrowding × Short-term ($BC_{15}$) | | −0.005 | | 0.003 | | | | | | | |
| 6. ΔCrowding × Short-term ($FT_{15}$) | | 0.011 | | −0.022* | | | | | | | |
| 7. ΔCrowding × Short-term ($NC_{15}$) | | −0.001 | | 0.009 | | | | | | | |
| 8. ΔCrowding × Switched | | 0.018 | | 0.003 | | | | | | | |
| 9. ΔStress | | | −0.096*** | −0.090*** | | | | | | | |
| 10. ΔHealth | | | | 0.093*** | | | | | | | |
| *User types* | | | | | | | | | | | |
| 11. Short-term ($Bus_{15}$) | | −0.005 | −0.011 | 0.005 | | | | | | | |
| 12. Short-term ($Car_{15}$) | | 0.005 | −0.003 | −0.002 | | | | | | | |
| 13. Short-term ($MC_{15}$) | | −0.010 | 0.013 | 0.014 | | | | | | | |
| 14. Short-term ($BC_{15}$) | | 0.005 | −0.011 | −0.003 | | | | | | | |
| 15. Short-term ($FT_{15}$) | | −0.005 | 0.003 | 0.039*** | | | | | | | |
| 16. Short-term ($NC_{15}$) | | 0.017 | 0.028** | −0.003 | | | | | | | |
| 17. Switched | | −0.002 | −0.003 | −0.017 | | | | | | | |
| Travel attributes | | | | | | | | | | | |
| 18. ΔCommuting time | 0.018 | 0.024** | −0.049*** | −0.018* | | | | | | | |
| Sociodemographic factors | | | | | | | | | | | |

**Table 5** (continued)

| | ΔCrowding | ΔStress | ΔHealth | ΔLS | Short-term ($Bus_{15}$) | Short-term ($Car_{15}$) | Short-term ($MC_{15}$) | Short-term ($BC_{15}$) | Short-term ($FT_{15}$) | Short-term ($NC_{15}$) | Switched |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 19. Δln(Household income) | −0.001 | −0.012 | 0.034*** | 0.027** | | | | | | | |
| 20. ΔHousehold size | 0.011 | −0.001 | −0.008 | 0.000 | | | | | | | |
| 21. $Age_{15}$ | | | | | 0.034*** | 0.002 | −0.009 | −0.032*** | 0.009 | 0.027** | −0.006 |
| 22. Female | | | | | 0.022* | −0.020* | −0.032*** | 0.036*** | 0.021* | 0.052*** | −0.009 |
| 23. Education | | | | | −0.018 | 0.015 | −0.022* | −0.027** | −0.004 | −0.006 | −0.046*** |
| 24. Household $income_{15}$ | | | | | −0.009 | −0.008 | −0.035*** | −0.039*** | 0.022* | −0.054*** | 0.012 |
| 25. Household $size_{15}$ | | | | | 0.009 | −0.030** | 0.015 | 0.029** | −0.036*** | 0.032*** | −0.022* |
| 26. Car $ownership_{15}$ | | | | | 0.001 | 0.157*** | 0.005 | 0.010 | −0.015 | −0.004 | −0.005 |
| 27. Attitude to crowding | | | | | −0.010 | 0.013 | 0.030*** | −0.010 | −0.009 | 0.018* | −0.009 |
| Major life events | | | | | | | | | | | |
| 28. Starting work | 0.000 | −0.005 | 0.010 | 0.006 | 0.024** | 0.027** | −0.007 | 0.034*** | −0.002 | −0.008 | 0.022** |
| 29. Restarting work | −0.010 | 0.009 | 0.019* | 0.017 | 0.015 | −0.004 | −0.011 | −0.002 | 0.000 | 0.180*** | 0.042*** |
| 30. Job-change | 0.022** | −0.033*** | −0.001 | 0.019* | −0.001 | 0.021** | 0.019* | 0.031*** | 0.018 | 0.029*** | 0.056*** |
| 31. Promotion | 0.023** | −0.014 | −0.019* | −0.006 | −0.002 | 0.026** | −0.002 | −0.001 | 0.003 | −0.017 | −0.001 |
| 32. Moving | 0.011 | 0.008 | 0.006 | 0.005 | 0.002 | 0.058*** | 0.000 | 0.022* | 0.031** | 0.012 | −0.054*** |
| 33. Marriage | 0.008 | 0.008 | 0.021* | 0.033*** | −0.007 | 0.006 | −0.008 | −0.009 | 0.020* | −0.014 | 0.007 |
| 34. Divorce | 0.001 | 0.019* | 0.012 | 0.026** | 0.017 | 0.009 | −0.004 | 0.001 | −0.009 | −0.001 | 0.014 |
| 35. Birth of child | 0.004 | 0.005 | −0.016 | −0.004 | −0.006 | 0.006 | 0.006 | −0.008 | −0.008 | 0.014 | −0.012 |
| 36. Traffic accident | 0.010 | 0.008 | −0.012 | −0.005 | 0.012 | 0.078*** | 0.008 | −0.003 | 0.006 | −0.009 | 0.005 |
| 37. Death within family | −0.002 | −0.009 | 0.000 | −0.010 | −0.002 | 0.003 | −0.002 | 0.013 | 0.012 | 0.013 | −0.015 |
| 38. Purchase of house | −0.014 | 0.016 | −0.001 | 0.022** | 0.007 | −0.011 | 0.013 | −0.011 | −0.003 | 0.008 | 0.006 |
| 39. Purchase of condominium | 0.005 | −0.015 | 0.009 | 0.014 | −0.004 | −0.027** | −0.005 | 0.010 | −0.019* | 0.013 | 0.001 |

*Crowding* dissatisfaction with in-vehicle crowding, *LS* life satisfactionn, *MC* motorcycle, *BC* bicycle, *FT* on foot, *NC* non-commuter

*$p<0.1$; **$p<0.05$; ***$p<0.01$

significant effects directly on life satisfaction among the switched group, similar to long-term train commuters.

The results of the coefficients of *Usertype* dummies indicate that life satisfaction increased if the respondents were short-term train commuters who commuted mainly by foot and that health status increased if the respondents were not commuters in 2015 (11th to 17th rows of Table 5).

Commuting time significantly increases the level of stress and decreases the levels of health and life satisfaction (18th row of Table 5), whereas higher income results in better health status and a higher degree of life satisfaction (19th row). While a job change or promotion increases the likelihood of being dissatisfied with crowding, some life events result in a better situation in terms of stress, health and life satisfaction (28th to 39th rows). However, a divorce causes stress, and experiencing a promotion results in a lower level of health.

Sociodemographic factors are the determinants of modal change and of becoming a short-term train commuter (21st to 27th rows of Table 5). Major life events are also significant predictors (28th to 39th rows). In particular, the results show that work-related life events and moving are major triggers to shifting one's commuting mode.

## Direct and indirect effects of dissatisfaction with in-vehicle crowding

We calculated the indirect effects of dissatisfaction with crowding on life satisfaction from the estimates of direct effects. The direct and indirect effects by group were calculated using the estimated coefficients shown in Table 5 by the following equations:

$$Direct_j = \beta_{L,1} + \beta_{L,2,j}, \tag{6}$$

$$Indirect_j = \left(\beta_{S,1} + \beta_{S,2,j}\right) \times \beta_{L,4} + \left(\beta_{S,1} + \beta_{S,2,j}\right) \times \beta_{H,1} \times \beta_{L,5}. \tag{7}$$

Here, $j$ refers to the following groups: the group of long-term train commuters; the 6 groups of short-term train commuters divided according to their previous commuting modes; and the group of commuters who switched from trains to other commuting modes. Before the calculation, we assumed that the statistically insignificant coefficients equaled zero. If a coefficient of an interaction term between dissatisfaction with crowding and a certain user type is insignificant, we recognize the effect for that user type as identical to that for long-term train commuters.

Table 6 shows the results of the calculation. A negative indirect effect of dissatisfaction with crowding on life satisfaction existed regardless of the types of users. On the other hand, direct effects existed among only some subgroups of short-term train commuters. Because a direct effect did not exist for the long-term train commuters, these effects were expected to disappear due to adaptation. In addition, because no significant direct effect was shown for the switched group, we did not observe the existence of the selection effect, the possibility that commuters experiencing strong effects from dissatisfaction with crowding switched from commuting by train to another mode.

**Table 6** Standardized direct and indirect effects of dissatisfaction with in-vehicle crowding on LS

| User type | Direct | Indirect |
|---|---|---|
| Long-term train commuters | – | – 0.0038 |
| Short-term train commuters ($Bus_{15}$) | – 0.019 | – 0.0038 |
| Short-term train commuters ($Car_{15}$) | – 0.024 | – 0.0038 |
| Short-term train commuters ($MC_{15}$) | – | – 0.0038 |
| Short-term train commuters ($BC_{15}$) | – | – 0.0038 |
| Short-term train commuters ($FT_{15}$) | – 0.022 | – 0.0038 |
| Short-term train commuters ($NC_{15}$) | – | – 0.0038 |
| Switched | – | – 0.0038 |

Only significant coefficients ($p < 0.1$) are used for calculation

*MC* motorcycle, *BC* bicycle, *FT* on foot, *NC* non-commuter

## Prefectural differences in Japan

Our analysis focused only on Tokyo, where both the train commuting rate and the level of in-vehicle crowding in trains are the highest in Japan; thus, the situation might differ in other cities depending on the city characteristics related to train commuting. We conducted a supplementary analysis in which our SEM model was applied to other prefectures in Japan. Figure 3 shows the rates of train commuting by prefecture, which were calculated using our survey data. Train commuting rates were especially high in the following three metropolitan areas: Greater Tokyo (including the prefectures around Tokyo prefecture), Keihanshin (around Osaka), and Chukyo (around Nagoya).

Figure 4 and Table 7 show the results of the prefectural analysis. Although the sample of train commuters was too small to analyze in most of the prefectures, the model fit the data well for Saitama, Chiba, Aichi, Osaka, and Hyogo prefectures. All these prefectures belong to three metropolitan areas. No prefectures except for Tokyo had both direct and indirect negative effects. We found a negative direct effect of dissatisfaction with crowding on life satisfaction among only short-term train commuters in Hyogo and a negative indirect effect of dissatisfaction with crowding on life satisfaction among all train commuters in Saitama. There was also a negative indirect effect among only short-term train commuters who previously commuted by car in Chiba. Moreover, there were positive direct effects of dissatisfaction with crowding among short-term train commuters in Saitama. The coefficients may have been affected by some outliers because of the somewhat small size of the subsample of short-term train commuters in Saitama (n($MC_{15} = 1$) = 16).

Negative effects of dissatisfaction with crowding were also found in other prefectures, similar to the case of Tokyo. In Saitama, regardless of the types of users, dissatisfaction with in-vehicle crowding had indirect negative effects on life satisfaction through stress and health. In Hyogo prefecture, which encompasses the sixth largest city in Japan, namely, Kobe City, the direct effects exist only for those who switched from commuting by car, bus, or walking to train commuting, but the effects disappeared with habituation, similar to the phenomenon in Tokyo.

In summary, there was generally no effect of dissatisfaction with crowding among commuters in the Keihanshin and Chukyo areas. Although there were direct effects on some commuters, these effects disappeared with habituation. In the greater Tokyo area, there

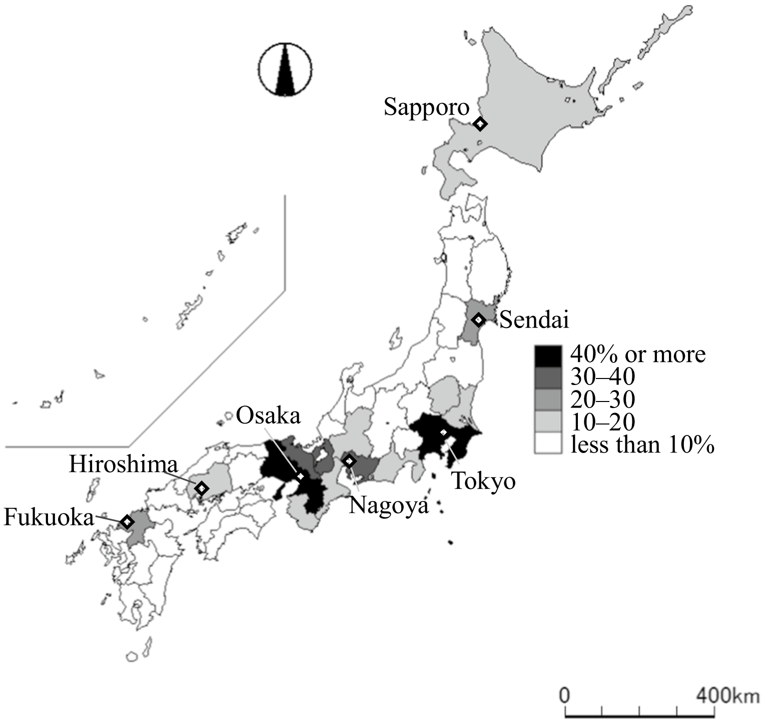


**Fig. 3** Train commuting rates by prefecture with the name of the major cities in Japan

were indirect effects of dissatisfaction with crowding through stress and health, which did not disappear with habituation.

In addition, the greater Tokyo area has a high proportion of dissatisfied train commuters. Figure 5 presents the average congestion rate of the major railway in each metropolitan area and the percentage of train commuters dissatisfied with in-vehicle crowding in each prefecture. According to this figure, train commuters seem more likely to be dissatisfied with in-vehicle crowding if they are in areas with higher congestion rates on the railway. This is especially true of the greater Tokyo area. On the basis of our results, in-vehicle crowding in the greater Tokyo area of Japan should be considered more seriously.

Despite the high level of in-vehicle crowdedness of trains, commuters in Osaka and Aichi (encompassing Nagoya) did not experience significant effects of dissatisfaction with crowding. There might be other determinants of whether dissatisfaction with crowding has a substantial effect, such as the personality of commuters. New interesting findings might be obtained by further analysis including other determinants of regional differences such as personality variables.

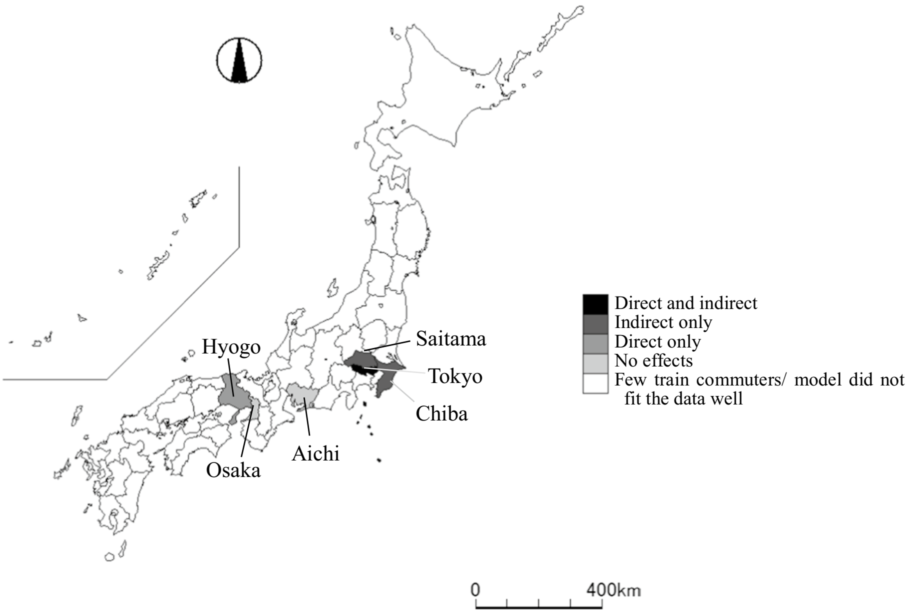


**Fig. 4** Effects of dissatisfaction with in-vehicle crowding on LS by prefecture in Japan

## Discussion

This study has the following two main findings: (1) Dissatisfaction with in-vehicle crowding directly lowers life satisfaction among short-term train commuters who previously commuted by bus, car or walking. (2) Dissatisfaction decreases life satisfaction indirectly through stress and health regardless of the types of transportation used. In our sample, direct effects were found on 50% of short-term train commuters but not on long-term train commuters. These results implied the possibility that the direct effects will disappear after commuting by train for a long time.

Why the direct effects disappear can, perhaps, be explained by the effects of the productive use of travel time. In the digital age, commuters can easily spend their in-vehicle time working, messaging, entertaining themselves, etc. by using electronic devices such as smartphones and laptop computers. Engaging in such activities makes commuting time more productive, thus reducing the disutility of travel time (Gripsrud and Hjorthol 2012; Wardman and Lyons 2016). Accordingly, commuters may adapt to in-vehicle crowding by being productive during the time spent commuting. Hence, all or part of the reduction in the direct effects can be attributed to the diminution of the disutility of travel on crowded train by using the travel time productively.

We did not observe a selection effect, the possibility that commuters experiencing strong direct effects from dissatisfaction with crowding have switched from commuting by train to another mode. In Tokyo, while 64% of workers commute mainly by train, only 3% of workers commute mainly by bus, and 8% commute by car (calculated using our survey data). This situation arises because of the inconvenience of all travel modes other than trains, such as the high parking price and the poor bus route options. Because of the low availability of other travel modes in Tokyo, dissatisfaction with crowding may not have substantial effects on mode switching.

**Table 7** Direct and indirect effects of dissatisfaction with in-vehicle crowding on LS by prefecture in Japan

| Prefecture | User type | Direct | Indirect | n | Rate of train commuters (%) |
|---|---|---|---|---|---|
| Saitama | Long-term | – | −0.0080 | 2204 | 57.1 |
| | Short-term ($Bus_{15}$) | – | −0.0080 | 24 | |
| | Short-term ($Car_{15}$) | – | −0.0080 | 81 | |
| | Short-term ($MC_{15}$) | 0.048 | −0.0080 | 16 | |
| | Short-term ($BC_{15}$) | – | −0.0080 | 55 | |
| | Short-term ($FT_{15}$) | – | −0.0080 | 39 | |
| | Short-term ($NC_{15}$) | – | −0.0080 | 58 | |
| | Switched | – | −0.0080 | 82 | |
| Chiba | Long-term | – | – | 2074 | 60.3 |
| | Short-term ($Bus_{15}$) | – | – | 20 | |
| | Short-term ($Car_{15}$) | – | −0.0045 | 85 | |
| | Short-term ($MC_{15}$) | – | – | 8 | |
| | Short-term ($BC_{15}$) | – | – | 47 | |
| | Short-term ($FT_{15}$) | – | – | 48 | |
| | Short-term ($NC_{15}$) | – | – | 55 | |
| | Switched | – | – | 61 | |
| Tokyo | Long-term | – | −0.0038 | 6970 | 70.0 |
| | Short-term ($Bus_{15}$) | −0.019 | −0.0038 | 123 | |
| | Short-term ($Car_{15}$) | −0.024 | −0.0038 | 159 | |
| | Short-term ($MC_{15}$) | – | −0.0038 | 34 | |
| | Short-term ($BC_{15}$) | – | −0.0038 | 268 | |
| | Short-term ($FT_{15}$) | −0.022 | −0.0038 | 260 | |
| | Short-term ($NC_{15}$) | – | −0.0038 | 232 | |
| | Switched | – | −0.0038 | 249 | |
| Aichi | Long-term | – | – | 1231 | 31.1 |
| | Short-term ($Bus_{15}$) | – | – | 38 | |
| | Short-term ($Car_{15}$) | – | – | 135 | |
| | Short-term ($MC_{15}$) | – | – | 14 | |
| | Short-term ($BC_{15}$) | – | – | 83 | |
| | Short-term ($FT_{15}$) | – | – | 30 | |
| | Short-term ($NC_{15}$) | – | – | 45 | |
| | Switched | – | – | 92 | |
| Osaka | Long-term | – | – | 2591 | 53.2 |
| | Short-term ($Bus_{15}$) | – | – | 51 | |
| | Short-term ($Car_{15}$) | – | – | 127 | |
| | Short-term ($MC_{15}$) | – | – | 35 | |
| | Short-term ($BC_{15}$) | – | – | 135 | |
| | Short-term ($FT_{15}$) | – | – | 87 | |
| | Short-term ($NC_{15}$) | – | – | 88 | |
| | Switched | – | – | 147 | |

**Table 7** (continued)

| Prefecture | User type | Direct | Indirect | n | Rate of train commuters (%) |
|---|---|---|---|---|---|
| Hyogo | Long-term | – | – | 1503 | 47.5 |
| | Short-term ($Bus_{15}$) | −0.039 | – | 35 | |
| | Short-term ($Car_{15}$) | −0.043 | – | 66 | |
| | Short-term ($MC_{15}$) | – | – | 17 | |
| | Short-term ($BC_{15}$) | – | – | 43 | |
| | Short-term ($FT_{15}$) | −0.042 | – | 31 | |
| | Short-term ($NC_{15}$) | – | – | 39 | |
| | Switched | – | – | 72 | |

Only significant coefficients ($p < 0.1$) are used for calculation for direct and indirect effects. The effects among long-term and short-term train commuters are shown separately only if there are significant differences among them. All models satisfy the following conditions: $\chi^2/df < 5$; SRMR < .05; CFI ≥ .89; RMSEA < .08

*MC* motorcycle, *FT* on foot

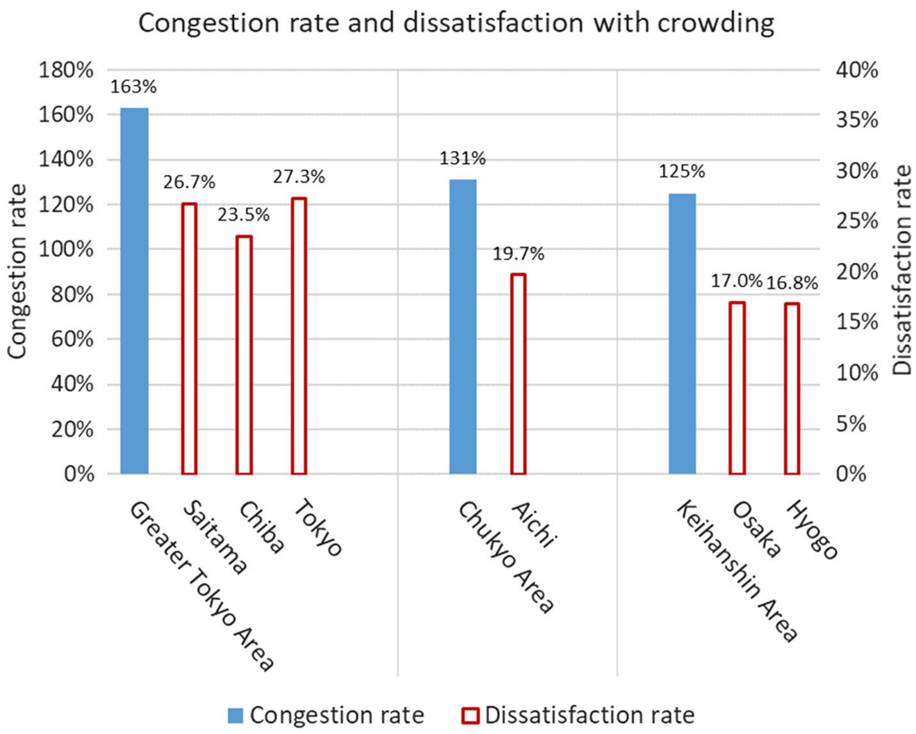


**Fig. 5** Average congestion rate of major railways in three metropolitan areas (MLIT 2018) and the percentage of train commuters dissatisfied with in-vehicle crowding (only for the prefectures shown in Table 7)

Despite the inconvenience of other travel modes in Tokyo, it is possible that commuters will be dissatisfied with crowding on trains when they shift from other modes to rail transportation. There is evidence that commuters tend to overestimate the effects of monetary aspects and underestimate the burden of physical and mental stress from commuting when they choose their commuting modes (Frey and Stutzer 2014). Based on these insights, we can assume that commuters underestimate the discomfort of in-vehicle crowding before a shift to rail, which would bring them stressful experiences of crowding that cannot be fully compensated by being freed from other types of inconvenience, such as high parking prices.

Our estimation implied that among short-term train commuters, the previous commuting mode determines whether dissatisfaction with crowding has direct effects on life satisfaction. The possible reason is that the past commuting experience might form an individual's reference point about commuting, and then, the commuter evaluates a new commuting method on the basis of the reference point. Car commuters may think that they can commute for long distances without any exposure to in-vehicle crowding. With this reference point, they may feel strongly dissatisfied with circumstances in which they must commute while dealing with serious in-vehicle crowdedness if they switch from a car to trains. For commuters who regularly walk to their workplace over relatively short distances with some flexibility, it will seem less flexible and stressful to commute on a crowded train for intermediate or long distances. On the other hand, new train commuters who were previously noncommuters might perceive in-vehicle crowding without a strong preconception because they do not seem to have a concrete reference point about commuting formed from daily experiences of regular commuting.

If this interpretation is correct, the direct effects of dissatisfaction with crowding can be regarded as the gap between a commuter's reference point and a new commuting situation immediately after switching their commuting mode. Furthermore, adaptation may also be defined as a change in the commuting reference point after a change in the commuting mode. However, it is difficult to explain the direct effects on commuters who previously commuted by bus, a similar travel mode to a train. Further analysis on the reference point for commuting would be useful for testing this assumption.

The main results of this study indicate that even if direct effects on SWB do not exist, the effects on people's health and stress subsist among not only short-term but also long-term train commuters. To avoid underestimating the value of the reduction in crowding, policy makers should also focus on indirect effects via stress and health conditions.

Most of the estimated effects of the main and control variables are consistent with those found in previous studies. The indirect effects of dissatisfaction with crowding are consistent with studies that investigated the relationship among crowding, stress and health (Cox et al. 2006; Mohd Mahudin et al. 2011, 2012). The results regarding commuting time are consistent with studies that found negative effects of commuting time on stress (Evans and Wener 2006), health (Christian 2012), and life satisfaction (Stutzer and Frey 2008). Our estimation showed similar results for the effects of income on health (Jones and Wildman 2008) and SWB (Stutzer 2004).

Although we found significant effects of commuting time on life satisfaction, previous studies, as well as our supplementary analysis, have inferred that the influence of commuting time differs from that of the previous commuting mode. Stutzer and Frey (2008) showed that a longer commuting time induces poorer life satisfaction by using data on workers that comprised a larger proportion of car commuters compared to our data. Wardman (2004) indicated that the value of time varies depending on travel modes, which leads to a variation in the marginal utility of time by modes. To test this variation, we conducted some supplementary analysis and investigated the variation in the effects of a commuting time change by the previous commuting modes. We eventually found that the respondents who commuted mainly by car in 2015 might be more sensitive to a commuting time change than the other respondents (Table 11, "Appendix"). While this supplementary model provided some interesting insight about the commuting time, the reliability seems somewhat poor because of the relatively low suitability of the model ($\chi^2$/df = 5.866 > 5; CFI = .866 < .90).

We also found inconsistent effects of sociodemographic variables on commuting mode in the previous year compared to existing studies of modal choice. For instance, our results show that travelers from smaller households are likely to have used a car for commuting in the previous year, while previous studies have found that travelers from larger households tend to commute by car (Ding et al. 2017). This different result may come from the characteristics of our sample that are different from those of previous studies: the choice of a regular commuting mode might be different from the commuting mode just before the mode shift.

Our findings have an implication for the difference in crowding cost estimation between SP and RP studies. There is some evidence that SP studies overestimate the cost of crowding, which we mentioned in the first section of the paper. This overestimation could be partially explained by adaptation. The possibility that respondents evaluated the condition of a travel mode that was different from what they regularly used was greater in SP studies than in RP studies, which focus on the travel mode that respondents actually use. Evaluating an unfamiliar in-vehicle condition may cause an overestimation of the effect of crowding in the SP studies. More studies should be conducted with RP methods, including sufficient individual characteristics for crowding cost estimation and for investigating adaptation to crowding.

Even if the direct effects were eliminated, there is a possibility that the effects will reappear due to some external cause such as an epidemic disease. When a communicable disease is being spread, people may become more sensitive to crowded situations, and thus the effects of dissatisfaction with crowding increase. In such an event, even a person who had once been accustomed to crowding will possibly suffer the direct effects again. In other words, the value of a reduction in crowding increases only temporally. Such a situation has become a reality due to the outbreak of the 2019 coronavirus disease (COVID-19), which emerged in Wuhan, China and has spread throughout the world. In fact, there are reports that some passengers contracted COVID-19 while traveling by public transport (e.g., Liu and Zhang 2020). It is also reported that at the beginning of May 2020, more than 80% of the Japanese population were worried about contracting COVID-19 (YouGov 2020).

When the epidemic disease is finally eliminated in Japan, the level of commuter dissatisfaction with crowding will likely remain higher than it was before the disease given that the concept of social distancing has become prevalent throughout the country. That said commuters behavior will partially, if not completely, return to what it was prior to the outbreak. Although the percentage of people in Tokyo who stopped commuting by train reached a peak of approximately 60% at the end of April 2020 (e.g., Tokyo Metropolitan Government 2020), commuters in Tokyo gradually began to return to normal in May 2020 (Asahi Shimbun Company, 2020). It is expected that even if the effects of dissatisfaction with crowding become stronger due to the epidemic, there will be little change in the behavioral level among commuters once the epidemic has passed.

Our study has some limitations. First, there is a possibility that reverse causality caused an endogeneity problem. The possible hypotheses are, for example, that a high level of stress causes a high probability of being dissatisfied with crowding or that low life satisfaction decreases an individual's health conditions. The first-difference estimation that we adopted can address only the endogeneity problem originating from time-invariant omitted variables. Therefore, another method, such as the instrumental variable approach, should be adopted in analyses to address potential reverse causality in the future, which could not be addressed in this study due to data availability.

Another limitation is the criterion used to classify the respondents as long-term or short-term train commuters. Our data cannot identify how many years are necessary to reduce the direct effects of dissatisfaction by adaptation. This study focused only on whether the respondents had commuted by train for at least one year. Longer-term surveys that track commuters for additional years can more precisely analyze how long it takes for commuters to become accustomed to commuting by train.

In addition, the extent of adaptation might be determined by factors such as the frequency of use, the objective level of crowding, past experiences with crowding in transportation, and how long commuters have not used such travel modes. Moreover, we cannot classify the adaptation that we found in the analysis as psychological or behavioral. Some commuters may "adapt" to train commuting by changing the time that they leave home and by avoiding rush hour.

One of the possible determinants that was not included but should be discussed is the probability of securing a seat on the train. The value of time savings for train commuters has been determined to be greater when they are standing as compared to when they are than sitting (Wardman and Whelan 2011). For train commuters who largely prefer sitting to standing, dissatisfaction with in-vehicle crowding would be mitigated if they could secure a seat. Recently, some railway companies have introduced reservation services that allow passengers to secure their seats during rush hour by paying an extra fee (Mainichi Newspapers, 2016). Such services have great potential for re-optimization among those commuters who are sensitive to standing and crowding, and accordingly, the level of dissatisfaction due to crowding can be reduced among train commuters as a whole.

In conclusion, this study has implied the possibility that adaptation can reduce the direct effects of dissatisfaction with in-vehicle crowding on SWB, which might not be the case for indirect effects through stress and health.

**Acknowledgements** This work was supported by the Grant in Aid from the Ministry of Education, Culture, Sports, Science and Technology in Japan (MEXT) JP20H00648, and Ministry of Environment, Japan. Any opinions, findings, and conclusions expressed in this material are those of the authors and do not necessarily reflect the views of the MEXT.

**Author contributions** JK: Conceptualization, Methodology, Formal analysis, Writing—Original Draft; MW: Conceptualization, Methodology, Writing—Review and Editing; SM: Resources, Supervision, Funding acquisition.

**Funding** This work was supported by the Grant in Aid from the Ministry of Education, Culture, Sports, Science and Technology in Japan (MEXT) JP20H00648.

**Data availability** Not applicable.

**Code availability** Not applicable.

## Compliance with ethical standards

**Conflicts of interest** On behalf of all authors, the corresponding author states that there is no conflict of interest.

## Appendix

See Tables 8, 9, 10 and 11.

**Table 8** Specification of hypothesized model (the first row shows the explained variables and the second and subsequent rows shows the explanatory variables)

| ΔCrowding | ΔStress | ΔHealth | ΔLS | Short-term ($Bus_{15}$) | Short-term ($Car_{15}$) |
|---|---|---|---|---|---|
| | ΔCrowding | | ΔCrowding | | |
| | ΔCrowding × $Bus_{15}$ | | ΔCrowding × $Bus_{15}$ | | |
| | ΔCrowding × $Car_{15}$ | | ΔCrowding × $Car_{15}$ | | |
| | ΔCrowding × $MC_{15}$ | | ΔCrowding × $MC_{15}$ | | |
| | ΔCrowding × $BC_{15}$ | | ΔCrowding × $BC_{15}$ | | |
| | ΔCrowding × $FT_{15}$ | | ΔCrowding × $FT_{15}$ | | |
| | ΔCrowding × $NC_{15}$ | | ΔCrowding × $NC_{15}$ | | |
| | ΔCrowding × Switched | | ΔCrowding × Switched | | |
| | | ΔStress | ΔStress | | |
| | | | ΔHealth | | |
| | Short-term ($Bus_{15}$) | Short-term ($Bus_{15}$) | Short-term ($Bus_{15}$) | | |
| | Short-term ($Car_{15}$) | Short-term ($Car_{15}$) | Short-term ($Car_{15}$) | | |
| | Short-term ($MC_{15}$) | Short-term ($MC_{15}$) | Short-term ($MC_{15}$) | | |
| | Short-term ($BC_{15}$) | Short-term ($BC_{15}$) | Short-term ($BC_{15}$) | | |
| | Short-term ($FT_{15}$) | Short-term ($FT_{15}$) | Short-term ($FT_{15}$) | | |
| | Short-term ($NC_{15}$) | Short-term ($NC_{15}$) | Short-term ($NC_{15}$) | | |
| | Switched | Switched | Switched | | |
| ΔCommuting time | ΔCommuting time | ΔCommuting time | ΔCommuting time | | |
| Δln(Household income) | Δln(Household income) | Δln(Household income) | Δln(Household income) | | |
| ΔHousehold size | ΔHousehold size | ΔHousehold size | ΔHousehold size | | |
| | | | | $Age_{15}$ | $Age_{15}$ |
| | | | | Female | Female |
| | | | | Education | Education |
| | | | | Household $income_{15}$ | Household $income_{15}$ |
| | | | | Household $size_{15}$ | Household $size_{15}$ |
| | | | | Car $ownership_{15}$ | Car $ownership_{15}$ |
| | | | | Attitude to crowding | Attitude to crowding |

**Table 8** (continued)

| ΔCrowding | ΔStress | ΔHealth | ΔLS | Short-term ($Bus_{15}$) | Short-term ($Car_{15}$) |
|---|---|---|---|---|---|
| Starting work | Starting work | Starting work | Starting work | Starting work | Starting work |
| Restarting work | Restarting work | Restarting work | Restarting work | Restarting work | Restarting work |
| Job-change | Job-change | Job-change | Job-change | Job-change | Job-change |
| Promotion | Promotion | Promotion | Promotion | Promotion | Promotion |
| Moving | Moving | Moving | Moving | Moving | Moving |
| Marriage | Marriage | Marriage | Marriage | Marriage | Marriage |
| Divorce | Divorce | Divorce | Divorce | Divorce | Divorce |
| Birth of child | Birth of child | Birth of child | Birth of child | Birth of child | Birth of child |
| Traffic accident | Traffic accident | Traffic accident | Traffic accident | Traffic accident | Traffic accident |
| Death within family | Death within family | Death within family | Death within family | Death within family | Death within family |
| Purchase of house | Purchase of house | Purchase of house | Purchase of house | Purchase of house | Purchase of house |
| Purchase of condominium | Purchase of condominium | Purchase of condominium | Purchase of condominium | Purchase of condominium | Purchase of condominium |

| Short-term ($MC_{15}$) | Short-term ($BC_{15}$) | Short-term ($FT_{15}$) | Short-term ($NC_{15}$) | Switched |
|---|---|---|---|---|
| $Age_{15}$ | $Age_{15}$ | $Age_{15}$ | $Age_{15}$ | $Age_{15}$ |
| Female | Female | Female | Female | Female |
| Education | Education | Education | Education | Education |
| Household $income_{15}$ | Household $income_{15}$ | Household $income_{15}$ | Household $income_{15}$ | Household $income_{15}$ |
| Household $size_{15}$ | Household $size_{15}$ | Household $size_{15}$ | Household $size_{15}$ | Household $size_{15}$ |
| Car $ownership_{15}$ | Car $ownership_{15}$ | Car $ownership_{15}$ | Car $ownership_{15}$ | Car $ownership_{15}$ |
| Attitude to crowding | Attitude to crowding | Attitude to crowding | Attitude to crowding | Attitude to crowding |
| Starting work | Starting work | Starting work | Starting work | Starting work |
| Restarting work | Restarting work | Restarting work | Restarting work | Restarting work |
| Job-change | Job-change | Job-change | Job-change | Job-change |
| Promotion | Promotion | Promotion | Promotion | Promotion |
| Moving | Moving | Moving | Moving | Moving |

**Table 8** (continued)

| Short-term ($MC_{15}$) | Short-term ($BC_{15}$) | Short-term ($FT_{15}$) | Short-term ($NC_{15}$) | Switched |
|---|---|---|---|---|
| Marriage | Marriage | Marriage | Marriage | Marriage |
| Divorce | Divorce | Divorce | Divorce | Divorce |
| Birth of child | Birth of child | Birth of child | Birth of child | Birth of child |
| Traffic accident | Traffic accident | Traffic accident | Traffic accident | Traffic accident |
| Death within family | Death within family | Death within family | Death within family | Death within family |
| Purchase of house | Purchase of house | Purchase of house | Purchase of house | Purchase of house |
| Purchase of condominium | Purchase of condominium | Purchase of condominium | Purchase of condominium | Purchase of condominium |

*Crowding* dissatisfaction with in-vehicle crowding, *LS* life satisfactionn, *MC* motorcycle, *BC* bicycle, *FT* on foot, *NC* non-commuter

**Table 9** Standardized coefficient estimates of the Model 1 (Direct)

| | ΔCrowding | ΔStress | ΔHealth | ΔLS | Short-term ($Bus_{15}$) | Short-term ($Car_{15}$) | Short-term ($MC_{15}$) | Short-term ($BC_{15}$) | Short-term ($FT_{15}$) | Short-term ($NC_{15}$) | Switched |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Main variables | | | | | | | | | | | |
| 1. ΔCrowding | | | | 0.006 | | | | | | | |
| 2. ΔCrowding × Short-term ($Bus_{15}$) | | | | −0.019* | | | | | | | |
| 3. ΔCrowding × Short-term ($Car_{15}$) | | | | −0.024** | | | | | | | |
| 4. ΔCrowding × Short-term ($MC_{15}$) | | | | −0.010 | | | | | | | |
| 5. ΔCrowding × Short-term ($BC_{15}$) | | | | 0.003 | | | | | | | |
| 6. ΔCrowding × Short-term ($FT_{15}$) | | | | −0.022* | | | | | | | |
| 7. ΔCrowding × Short-term ($NC_{15}$) | | | | 0.009 | | | | | | | |
| 8. ΔCrowding × Switched | | | | 0.003 | | | | | | | |
| 9. ΔStress | | | −0.096*** | −0.090*** | | | | | | | |
| 10. ΔHealth | | | | 0.093*** | | | | | | | |
| User types | | | | | | | | | | | |
| 11. Short-term ($Bus_{15}$) | | −0.004 | −0.011 | 0.005 | | | | | | | |
| 12. Short-term ($Car_{15}$) | | 0.007 | −0.003 | −0.002 | | | | | | | |
| 13. Short-term ($MC_{15}$) | | −0.011 | 0.013 | 0.014 | | | | | | | |
| 14. Short-term ($BC_{15}$) | | 0.003 | −0.011 | −0.003 | | | | | | | |
| 15. Short-term ($FT_{15}$) | | −0.001 | 0.003 | 0.039*** | | | | | | | |
| 16. Short-term ($NC_{15}$) | | 0.017 | 0.028** | −0.003 | | | | | | | |
| 17. Switched | | −0.003 | −0.003 | −0.017 | | | | | | | |
| Travel attributes | | | | | | | | | | | |
| 18. ΔCommuting time | 0.018 | 0.025** | −0.049*** | −0.018* | | | | | | | |
| Sociodemographic factors | | | | | | | | | | | |
| 19. Δln(Household income) | −0.001 | −0.013 | 0.034*** | 0.027** | | | | | | | |

**Table 9** (continued)

| | ΔCrowding | ΔStress | ΔHealth | ΔLS | Short-term ($Bus_{15}$) | Short-term ($Car_{15}$) | Short-term ($MC_{15}$) | Short-term ($BC_{15}$) | Short-term ($FT_{15}$) | Short-term ($NC_{15}$) | Switched |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 20. ΔHousehold size | 0.011 | −0.001 | −0.008 | 0.000 | | | | | | | |
| 21. $Age_{15}$ | | | | | 0.034*** | 0.002 | −0.009 | −0.032*** | 0.009 | 0.027** | −0.006 |
| 22. Female | | | | | 0.022* | −0.020* | −0.032*** | 0.036*** | 0.021* | 0.052*** | −0.009 |
| 23. Education | | | | | −0.018 | 0.015 | −0.022* | −0.027** | −0.004 | −0.006 | −0.046*** |
| 24. Household $income_{15}$ | | | | | −0.009 | −0.008 | −0.035*** | −0.039*** | 0.022* | −0.054*** | 0.012 |
| 25. Household $size_{15}$ | | | | | 0.009 | −0.030** | 0.015 | 0.029** | −0.036*** | 0.032*** | −0.022* |
| 26. Car $ownership_{15}$ | | | | | 0.001 | 0.157*** | 0.005 | 0.010 | −0.015 | −0.004 | −0.005 |
| 27. Attitude to crowding | | | | | −0.010 | 0.013 | 0.030*** | −0.010 | −0.009 | 0.018* | −0.009 |
| Major life events | | | | | | | | | | | |
| 28. Starting work | 0.000 | −0.004 | 0.010 | 0.006 | 0.024** | 0.027** | −0.007 | 0.034*** | −0.002 | −0.008 | 0.022** |
| 29. Restarting work | −0.010 | 0.008 | 0.019* | 0.017 | 0.015 | −0.004 | −0.011 | −0.002 | 0.000 | 0.180*** | 0.042*** |
| 30. Job-change | 0.022** | −0.032*** | −0.001 | 0.019* | −0.001 | 0.021** | 0.019* | 0.031*** | 0.018 | 0.029*** | 0.056*** |
| 31. Promotion | 0.023** | −0.013 | −0.019* | −0.006 | −0.002 | 0.026** | −0.002 | −0.001 | 0.003 | −0.017 | −0.001 |
| 32. Moving | 0.011 | 0.008 | 0.006 | 0.005 | 0.002 | 0.058*** | 0.000 | 0.022* | 0.031** | 0.012 | −0.054*** |
| 33. Marriage | 0.008 | 0.009 | 0.021* | 0.033*** | −0.007 | 0.006 | −0.008 | −0.009 | 0.020* | −0.014 | 0.007 |
| 34. Divorce | 0.001 | 0.019* | 0.012 | 0.026** | 0.017 | 0.009 | −0.004 | 0.001 | −0.009 | −0.001 | 0.014 |
| 35. Birth of child | 0.004 | 0.005 | −0.016 | −0.004 | −0.006 | 0.006 | 0.006 | −0.008 | −0.008 | 0.014 | −0.012 |
| 36. Traffic accident | 0.010 | 0.009 | −0.012 | −0.005 | 0.012 | 0.078*** | 0.008 | −0.003 | 0.006 | −0.009 | 0.005 |
| 37. Death within family | −0.002 | −0.009 | 0.000 | −0.010 | −0.002 | 0.003 | −0.002 | 0.013 | 0.012 | 0.013 | −0.015 |
| 38. Purchase of house | −0.014 | 0.015 | −0.001 | 0.022** | 0.007 | −0.011 | 0.013 | −0.011 | −0.003 | 0.008 | 0.006 |
| 39. Purchase of condominium | 0.005 | −0.014 | 0.009 | 0.014 | −0.004 | −0.027** | −0.005 | 0.010 | −0.019* | 0.013 | 0.001 |

*Crowding* dissatisfaction with in-vehicle crowding, *LS* life satisfactionn, *MC* motorcycle, *BC* bicycle, *FT* on foot, *NC* non-commuter

*$p<0.1$; **$p<0.05$; ***$p<0.01$

**Table 10** Standardized coefficient estimates of the Model 2 (Indirect)

| | ΔCrowding | ΔStress | ΔHealth | ΔLS | Short-term ($Bus_{15}$) | Short-term ($Car_{15}$) | Short-term ($MC_{15}$) | Short-term ($BC_{15}$) | Short-term ($FT_{15}$) | Short-term ($NC_{15}$) | Switched |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Main variables | | | | | | | | | | | |
| 1. ΔCrowding | | 0.039*** | | | | | | | | | |
| 2. ΔCrowding × Short-term ($Bus_{15}$) | | 0.008 | | | | | | | | | |
| 3. ΔCrowding × Short-term ($Car_{15}$) | | 0.002 | | | | | | | | | |
| 4. ΔCrowding × Short-term ($MC_{15}$) | | −0.007 | | | | | | | | | |
| 5. ΔCrowding × Short-term ($BC_{15}$) | | −0.005 | | | | | | | | | |
| 6. ΔCrowding × Short-term ($FT_{15}$) | | 0.011 | | | | | | | | | |
| 7. ΔCrowding × Short-term ($NC_{15}$) | | −0.001 | | | | | | | | | |
| 8. ΔCrowding × Switched | | 0.018 | | | | | | | | | |
| 9. ΔStress | | | −0.096*** | −0.090*** | | | | | | | |
| 10. ΔHealth | | | | 0.093*** | | | | | | | |
| User types | | | | | | | | | | | |
| 11. Short-term ($Bus_{15}$) | | −0.005 | −0.011 | 0.003 | | | | | | | |
| 12. Short-term ($Car_{15}$) | | 0.005 | −0.003 | −0.009 | | | | | | | |
| 13. Short-term ($MC_{15}$) | | −0.010 | 0.013 | 0.012 | | | | | | | |
| 14. Short-term ($BC_{15}$) | | 0.005 | −0.011 | −0.002 | | | | | | | |
| 15. Short-term ($FT_{15}$) | | −0.005 | 0.003 | 0.034*** | | | | | | | |
| 16. Short-term ($NC_{15}$) | | 0.017 | 0.028** | 0.000 | | | | | | | |
| 17. Switched | | −0.002 | −0.003 | −0.017 | | | | | | | |
| Travel attributes | | | | | | | | | | | |
| 18. ΔCommuting time | 0.018 | 0.024** | −0.049*** | −0.019* | | | | | | | |

**Table 10** (continued)

| | ΔCrowding | ΔStress | ΔHealth | ΔLS | Short-term ($Bus_{15}$) | Short-term ($Car_{15}$) | Short-term ($MC_{15}$) | Short-term ($BC_{15}$) | Short-term ($FT_{15}$) | Short-term ($NC_{15}$) | Switched |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Sociodemographic factors | | | | | | | | | | | |
| 19. Δln(Household income) | −0.001 | −0.012 | 0.034*** | 0.026** | | | | | | | |
| 20. ΔHousehold size | 0.011 | −0.001 | −0.008 | 0.001 | | | | | | | |
| 21. $Age_{15}$ | | | | | 0.034*** | 0.002 | −0.009 | −0.032*** | 0.009 | 0.027** | −0.006 |
| 22. Female | | | | | 0.022* | −0.020* | −0.032*** | 0.036*** | 0.021* | 0.052*** | −0.009 |
| 23. Education | | | | | −0.018 | 0.015 | −0.022* | −0.027** | −0.004 | −0.006 | −0.046*** |
| 24. Household $income_{15}$ | | | | | −0.009 | −0.008 | −0.035*** | −0.039*** | 0.022* | −0.054*** | 0.012 |
| 25. Household $size_{15}$ | | | | | 0.009 | −0.030** | 0.015 | 0.029** | −0.036*** | 0.032*** | −0.022* |
| 26. Car $ownership_{15}$ | | | | | 0.001 | 0.157*** | 0.005 | 0.010 | −0.015 | −0.004 | −0.005 |
| 27. Attitude to crowding | | | | | −0.010 | 0.013 | 0.030*** | −0.010 | −0.009 | 0.018* | −0.009 |
| Major life events | | | | | | | | | | | |
| 28. Starting work | 0.000 | −0.005 | 0.010 | 0.006 | 0.024** | 0.027** | −0.007 | 0.034*** | −0.002 | −0.008 | 0.022** |
| 29. Restarting work | −0.010 | 0.009 | 0.019* | 0.017 | 0.015 | −0.004 | −0.011 | −0.002 | 0.000 | 0.180*** | 0.042*** |
| 30. Job-change | 0.022** | −0.033*** | −0.001 | 0.019* | −0.001 | 0.021** | 0.019* | 0.031*** | 0.018 | 0.029*** | 0.056*** |
| 31. Promotion | 0.023** | −0.014 | −0.019* | −0.005 | −0.002 | 0.026** | −0.002 | −0.001 | 0.003 | −0.017 | −0.001 |
| 32. Moving | 0.011 | 0.008 | 0.006 | 0.004 | 0.002 | 0.058*** | 0.000 | 0.022* | 0.031** | 0.012 | −0.054*** |
| 33. Marriage | 0.008 | 0.008 | 0.021* | 0.033*** | −0.007 | 0.006 | −0.008 | −0.009 | 0.020* | −0.014 | 0.007 |
| 34. Divorce | 0.001 | 0.019* | 0.012 | 0.026** | 0.017 | 0.009 | −0.004 | 0.001 | −0.009 | −0.001 | 0.014 |
| 35. Birth of child | 0.004 | 0.005 | −0.016 | −0.005 | −0.006 | 0.006 | 0.006 | −0.008 | −0.008 | 0.014 | −0.012 |
| 36. Traffic accident | 0.010 | 0.008 | −0.012 | −0.005 | 0.012 | 0.078*** | 0.008 | −0.003 | 0.006 | −0.009 | 0.005 |
| 37. Death within family | −0.002 | −0.009 | 0.000 | −0.011 | −0.002 | 0.003 | −0.002 | 0.013 | 0.012 | 0.013 | −0.015 |
| 38. Purchase of house | −0.014 | 0.016 | −0.001 | 0.022* | 0.007 | −0.011 | 0.013 | −0.011 | −0.003 | 0.008 | 0.006 |
| 39. Purchase of condominium | 0.005 | −0.015 | 0.009 | 0.014 | −0.004 | −0.027** | −0.005 | 0.010 | −0.019* | 0.013 | 0.001 |

*Crowding* dissatisfaction with in-vehicle crowding, *LS* life satisfactionn, *MC* motorcycle, *BC* bicycle, *FT* on foot, *NC* non-commuter

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

**Table 11** Standardized coefficient estimates of the hypothesized model with the effects of commuting time different by previous modes

| | ΔCrowding | ΔStress | ΔHealth | ΔLS | Short-term ($Bus_{15}$) | Short-term ($Car_{15}$) | Short-term ($MC_{15}$) | Short-term ($BC_{15}$) | Short-term ($FT_{15}$) | Short-term ($NC_{15}$) | Switched |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Main variables | | | | | | | | | | | |
| 1. ΔCrowding | | 0.039*** | | 0.006 | | | | | | | |
| 2. ΔCrowding × Short-term ($Bus_{15}$) | | 0.007 | | −0.019* | | | | | | | |
| 3. ΔCrowding × Short-term ($Car_{15}$) | | 0.001 | | −0.023** | | | | | | | |
| 4. ΔCrowding × Short-term ($MC_{15}$) | | −0.007 | | −0.010 | | | | | | | |
| 5. ΔCrowding × Short-term ($BC_{15}$) | | −0.005 | | 0.003 | | | | | | | |
| 6. ΔCrowding × Short-term ($FT_{15}$) | | 0.012 | | −0.022* | | | | | | | |
| 7. ΔCrowding × Short-term ($NC_{15}$) | | −0.001 | | 0.010 | | | | | | | |
| 8. ΔCrowding × Switched | | 0.018 | | 0.002 | | | | | | | |
| 9. ΔStress | | | −0.096*** | −0.089*** | | | | | | | |
| 10. ΔHealth | | | | 0.092*** | | | | | | | |
| User types | | | | | | | | | | | |
| 11. Short-term ($Bus_{15}$) | | −0.004 | −0.011 | 0.004 | | | | | | | |
| 12. Short-term ($Car_{15}$) | | 0.002 | 0.001 | 0.004 | | | | | | | |
| 13. Short-term ($MC_{15}$) | | −0.010 | 0.013 | 0.013 | | | | | | | |
| 14. Short-term ($BC_{15}$) | | 0.005 | −0.012 | −0.004 | | | | | | | |
| 15. Short-term ($FT_{15}$) | | −0.005 | 0.002 | 0.039*** | | | | | | | |
| 16. Short-term ($NC_{15}$) | | 0.019* | 0.025** | −0.006 | | | | | | | |
| 17. Switched | | −0.003 | −0.003 | −0.016 | | | | | | | |
| Travel attributes | | | | | | | | | | | |
| 18. ΔCommuting time | 0.018 | 0.016 | −0.039*** | −0.006 | | | | | | | |
| 19. ΔCommuting time × $Car_{15}$ | | 0.028** | −0.034*** | −0.044*** | | | | | | | |

**Table 11** (continued)

| | ΔCrowding | ΔStress | ΔHealth | ΔLS | Short-term ($Bus_{15}$) | Short-term ($Car_{15}$) | Short-term ($MC_{15}$) | Short-term ($BC_{15}$) | Short-term ($FT_{15}$) | Short-term ($NC_{15}$) | Switched |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Sociodemographic factors | | | | | | | | | | | |
| 20. Δln(Household income) | −0.001 | −0.013 | 0.035*** | 0.028** | | | | | | | |
| 21. ΔHousehold size | 0.011 | −0.002 | −0.006 | 0.003 | | | | | | | |
| 22. $Age_{15}$ | | | | | 0.034*** | 0.002 | −0.009 | −0.032*** | 0.009 | 0.027** | −0.006 |
| 23. Female | | | | | 0.022* | −0.020* | −0.032*** | 0.036*** | 0.021* | 0.052*** | −0.009 |
| 24. Education | | | | | −0.018 | 0.015 | −0.022* | −0.027** | −0.004 | −0.006 | −0.046*** |
| 25. Household $income_{15}$ | | | | | −0.009 | −0.008 | −0.035*** | −0.039*** | 0.022* | −0.054*** | 0.012 |
| 26. Household $size_{15}$ | | | | | 0.009 | −0.030** | 0.015 | 0.029** | −0.036*** | 0.032*** | −0.022* |
| 27. Car $ownership_{15}$ | | | | | 0.001 | 0.157*** | 0.005 | 0.010 | −0.015 | −0.004 | −0.005 |
| 28. Attitude to crowding | | | | | −0.010 | 0.013 | 0.030*** | −0.010 | −0.009 | 0.018* | −0.009 |
| Major life events | | | | | | | | | | | |
| 29. Starting work | 0.000 | −0.007 | 0.013 | 0.009 | 0.024** | 0.027** | −0.007 | 0.034*** | −0.002 | −0.008 | 0.022** |
| 30. Restarting work | −0.010 | 0.007 | 0.021* | 0.019* | 0.015 | −0.004 | −0.011 | −0.002 | 0.000 | 0.180*** | 0.042*** |
| 31. Job-change | 0.022** | −0.033*** | −0.001 | 0.020* | −0.001 | 0.021** | 0.019* | 0.031*** | 0.018 | 0.029*** | 0.056*** |
| 32. Promotion | 0.023** | −0.014 | −0.018* | −0.004 | −0.002 | 0.026** | −0.002 | −0.001 | 0.003 | −0.017 | −0.001 |
| 33. Moving | 0.011 | 0.008 | 0.006 | 0.005 | 0.002 | 0.058*** | 0.000 | 0.022* | 0.031** | 0.012 | −0.054*** |
| 34. Marriage | 0.008 | 0.007 | 0.022** | 0.034*** | −0.007 | 0.006 | −0.008 | −0.009 | 0.020* | −0.014 | 0.007 |
| 35. Divorce | 0.001 | 0.017 | 0.015 | 0.030*** | 0.017 | 0.009 | −0.004 | 0.001 | −0.009 | −0.001 | 0.014 |
| 36. Birth of child | 0.004 | 0.004 | −0.015 | −0.003 | −0.006 | 0.006 | 0.006 | −0.008 | −0.008 | 0.014 | −0.012 |
| 37. Traffic accident | 0.010 | 0.007 | −0.010 | −0.002 | 0.012 | 0.078*** | 0.008 | −0.003 | 0.006 | −0.009 | 0.005 |
| 38. Death within family | −0.002 | −0.010 | 0.001 | −0.009 | −0.002 | 0.003 | −0.002 | 0.013 | 0.012 | 0.013 | −0.015 |
| 39. Purchase of house | −0.014 | 0.014 | 0.001 | 0.025** | 0.007 | −0.011 | 0.013 | −0.011 | −0.003 | 0.008 | 0.006 |
| 40. Purchase of condominium | 0.005 | −0.017 | 0.011 | 0.017 | −0.004 | −0.027** | −0.005 | 0.010 | −0.019* | 0.013 | 0.001 |

$\chi^2$/df = 5.866; SRMR = .011; CFI = .866; RMSEA = .024; AIC = 173,957.623

*Crowding* dissatisfaction with in-vehicle crowding, *LS* life satisfactionn, *MC* motorcycle, *BC* bicycle, *FT* on foot, *NC* non-commuter

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

## References


Abou-Zeid, M., Witter, R., Bierlaire, M., Kaufmann, V., Ben-Akiva, M.: Happiness and travel mode switching: findings from a Swiss public transportation experiment. Transp. Policy **19**(1), 93–104 (2012). https://doi.org/10.1016/j.tranpol.2011.09.009

Asahi Shimbun Company: With state of emergency lifted, is Tokyo going back to normal? The Asahi Shimbun. May 27, 2020. http://www.asahi.com/ajw/articles/13407969 (2020). Accessed 7 June 2020

Basu, D., Hunt, J.D.: Valuing of attributes influencing the attractiveness of suburban train service in Mumbai city: A stated preference approach. Transp. Res. Part A Policy Pract. **46**(9), 1465–1476 (2012). https://doi.org/10.1016/j.tra.2012.05.010

Batarce, M., Muñoz, J.C., Ortúzar, J.D.: Valuing crowding in public transport: Implications for cost-benefit analysis. Transp. Res. Part A Policy Pract. **91**, 358–378 (2016). https://doi.org/10.1016/j.tra.2016.06.025

Belgiawan, P.F., Schmöcker, J.D., Fujii, S.: Understanding car ownership motivations among Indonesian students. Int. J Sustain. Transp. **10**(4), 295–307 (2016). https://doi.org/10.1080/15568318.2014.921846

Bergstad, C.J., Gamble, A., Gärling, T., Hagman, O., Polk, M., Ettema, D., Friman, M., Olsson, L.E.: Subjective well-being related to satisfaction with daily travel. Transportation **38**(1), 1–15 (2011). https://doi.org/10.1007/s11116-010-9283-z

Björklund, G., Swärdh, J.-E.: Estimating policy values for in-vehicle comfort and crowding reduction in local public transport. Transp. Res. Part A Policy Pract. **106**, 453–472 (2017). https://doi.org/10.1016/j.tra.2017.10.016

Bollen, K.A.: Structural equations with latent variables. Willey, Hoboken (1989)

Brown, T.A.: Confirmatory Factor Analysis for Applied Research. Methodology in the Social Sciences. The Guilford Press, New York (2006)

Christian, T.J.: Trade-offs between commuting time and health-related activities. J. Urban Health **89**(5), 746–757 (2012). https://doi.org/10.1007/s11524-012-9678-6

Clark, B., Chatterjee, K., Melia, S.: Changes to commute mode: the role of life events, spatial context and environmental attitude. Transp. Res. Part A Policy Pract. **89**, 89–105 (2016). https://doi.org/10.1016/j.tra.2016.05.005

Cox, T., Houdmont, J., Griffiths, A.: Rail passenger crowding, stress, health and safety in Britain. Transp. Res. Part A Policy Pract. **40**(3), 244–258 (2006). https://doi.org/10.1016/j.tra.2005.07.001

Currie, J., Walker, R.: Traffic congestion and infant health: evidence from E-ZPass. Am. Econ. J. Appl. Econ. **3**(1), 65–90 (2011)

de Oña, J., de Oña, R.: Quality of service in public transport based on customer satisfaction surveys: a review and assessment of methodological approaches. Transp. Sci. **49**(3), 605–622 (2014). https://doi.org/10.1287/trsc.2014.0544

de Oña, J., de Oña, R., Eboli, L., Mazzulla, G.: Perceived service quality in bus transit service: a structural equation approach. Transp. Policy **29**, 219–226 (2013). https://doi.org/10.1016/j.tranpol.2013.07.001

de Palma, A., Lindsey, R., Monchambert, G.: The economics of crowding in rail transit. J. Urban Econ. **101**, 106–122 (2017). https://doi.org/10.1016/j.jue.2017.06.003

De Vos, J.: Analysing the effect of trip satisfaction on satisfaction with the leisure activity at the destination of the trip, in relationship with life satisfaction. Transportation **46**(3), 623–645 (2019). https://doi.org/10.1007/s11116-017-9812-0

De Vos, J., Witlox, F.: Travel satisfaction revisited. On the pivotal role of travel satisfaction in conceptualising a travel behaviour process. Transp. Res. Part A Policy Pract. **106**, 364–373 (2017). https://doi.org/10.1016/j.tra.2017.10.009

dell'Olio, L., Ibeas, A., Cecín, P.: Modelling user perception of bus transit quality. Transp. Policy **17**(6), 388–397 (2010). https://doi.org/10.1016/j.tranpol.2010.04.006

Ding, C., Wang, D., Liu, C., Zhang, Y., Yang, J.: Exploring the influence of built environment on travel mode choice considering the mediating effects of car ownership and travel distance. Transp. Res. Part A Policy Pract. **100**, 65–80 (2017). https://doi.org/10.1016/j.tra.2017.04.008

Eboli, L., Mazzulla, G.: Relationships between rail passengers' satisfaction and service quality: a framework for identifying key service factors. Public Transport **7**(2), 185–201 (2015). https://doi.org/10.1007/s12469-014-0096-x

Ettema, D., Gärling, T., Olsson, L.E., Friman, M.: Out-of-home activities, daily travel, and subjective well-being. Transp. Res. Part A Policy Pract. **44**(9), 723–732 (2010). https://doi.org/10.1016/j.tra.2010.07.005

Evans, G.W., Wener, R.E.: Rail commuting duration and passenger stress. Health Psychol. **25**(3), 408–412 (2006). https://doi.org/10.1037/0278-6133.25.3.408

Frey, B.S., Stutzer, A.: Economic consequences of mispredicting utility. J. Happiness Stud. **15**(4), 937–956 (2014). https://doi.org/10.1007/s10902-013-9457-4

Friman, M., Gärling, T., Ettema, D., Olsson, L.E.: How does travel affect emotional well-being and life satisfaction? Transp. Res. Part A Policy Pract. **106**(September), 170–180 (2017). https://doi.org/10.1016/j.tra.2017.09.024

Golob, T.F.: Structural equation modeling for travel behavior research. Transp. Res. Part B Methodol. **37**(1), 1–25 (2003). https://doi.org/10.1016/S0191-2615(01)00046-7

Greenwood, D.C., Muir, K.R., Packham, C.J., Madeley, R.J.: Coronary heart disease: a review of the role of psychosocial stress and social support. J. Public Health **18**(2), 221–231 (1996). https://doi.org/10.1093/oxfordjournals.pubmed.a024483

Gripsrud, M., Hjorthol, R.: Working on the train: from 'dead time' to productive and vital time. Transportation **39**, 941–956 (2012). https://doi.org/10.1007/s11116-012-9396-7

Halvorsen, A., Koutsopoulos, H.N., Lau, S., Au, T., Zhao, J.: Reducing subway crowding: analysis of an off-peak discount experiment in Hong Kong. Transp. Res. Rec. J. Transp. Res. Board **2544**(1), 38–46 (2016). https://doi.org/10.3141/2544-05

Han, C., Phillips, P.C.B.: First difference maximum likelihood and dynamic panel estimation. J. Econom. **175**(1), 35–45 (2013). https://doi.org/10.1016/j.jeconom.2013.03.003

Haywood, L., Koning, M.: The distribution of crowding costs in public transport: new evidence from Paris. Transp. Res. Part A Policy Pract. **77**, 182–201 (2015). https://doi.org/10.1016/j.tra.2015.04.005

Haywood, L., Koning, M., Monchambert, G.: Crowding in public transport: who cares and why? Transp. Res. Part A Policy Pract. **100**, 215–227 (2017). https://doi.org/10.1016/j.tra.2017.04.022

Haywood, L., Koning, M., Prud'homme, R.: The economic cost of subway congestion: estimates from Paris. Econ. Transp. **14**, 1–8 (2018). https://doi.org/10.1016/j.ecotra.2017.10.001

Honda, Y.: The formation and transformation of the Japanese system on transition from school to work. Soc. Sci. Jpn. J. **7**(1), 103–115 (2004). https://doi.org/10.1093/ssjj/7.1.103

Hörcher, D., Graham, D.J., Anderson, R.J.: Crowding cost estimation with large scale smart card and vehicle location data. Transp. Res. Part B Methodol. **95**, 105–125 (2017). https://doi.org/10.1016/j.trb.2016.10.015

Iso, H., Date, C., Yamamoto, A., Toyoshima, H., Tanabe, N., Kikuchi, S., Kondo, T., Watanabe, Y., Wada, Y., Ishibashi, T., Suzuki, H., Koizumi, A., Inaba, Y., Tamakoshi, A., Ohno, Y., Mori, M., Motohashi, Y., Hisamichi, S., Nakamura, Y., Mikami, H., Hashimoto, S., Hoshiyama, Y., Shimizu, H., Tokudome, S., Ito, Y., Kawamura, T., Nakao, M., Suzuki, T., Hashimoto, T., Nose, T., Hayakawa, N., Yoshimura, T., Fukuda, K., Okamoto, N., Shio, H., Kitagawa, T., Kuroki, T., Tajima, K.: Perceived mental stress and mortality from cardiovascular disease among Japanese men and women: The Japan Collaborative Cohort Study for Evaluation of Cancer Risk Sponsored by Monbusho (JACC Study). Circulation **106**(10), 1229–1236 (2002). https://doi.org/10.1161/01.CIR.0000028145.58654.41

Johnson, D.: Two-wave panel analysis: comparing statistical methods for studying the effects of transitions. J. Marriage Fam. **67**(4), 1061–1075 (2005). https://doi.org/10.1111/j.1741-3737.2005.00194.x

Jones, A.M., Wildman, J.: Health, income and relative deprivation: evidence from the BHPS. J. Health Econ. **27**(2), 308–324 (2008). https://doi.org/10.1016/j.jhealeco.2007.05.007

Kahneman, D., Wakker, P.P., Rakesh, S.: Back to Bentham? Explorations of experienced utility. Q. J. Econ. **112**(2), 375–405 (1997)

Kato, H., Itoh, M., Kato, S., Ishida, H.: Cost-benefit analysis for improvement of transfer at urban railway stations. In: World Transport Research: Selected Proceedings of the 9th World Conference on Transport Research (2003)

Kawaguchi, D., Ueno, Y.: Declining long-term employment in Japan. J. Jpn. Int. Econ. **28**, 19–36 (2013). https://doi.org/10.1016/j.jjie.2013.01.005

Kennedy, D.P., Gläscher, J., Tyszka, J.M., Adolphs, R.: Personal space regulation by the human amygdala. Nat. Neurosci. **12**(10), 1226–1227 (2009). https://doi.org/10.1038/nn.2381

Kidokoro, Y.: Regulatory reform and the congestion of urban railways. Transp. Res. Part A Policy Pract. **40**(1), 52–73 (2006). https://doi.org/10.1016/j.tra.2005.04.003

Kripfganz, S.: Quasi–maximum likelihood estimation of linear dynamic short-T panel-data models. Stata J. **16**(4), 1013–1038 (2016). https://doi.org/10.1177/1536867X1601600411

Liu, X., Zhang, S.: COVID-19: face masks and human-to-human transmission. Influenza Other Respir. Viruses (2020). https://doi.org/10.1111/irv.12740

Lucas, R.E.: Adaptation and the set-point model of subjective well-being. Curr. Dir. Psychol. Sci. **16**(2), 75–79 (2007). https://doi.org/10.1111/j.1467-8721.2007.00479.x

Mainichi Newspapers: Tokyo rail companies compete to provide premium seating to avoid rush hour crowds. *Mainichi*, Jan 2, 2016. https://mainichi.jp/english/articles/20160102/p2a/00m/0na/004000c (2016). Accessed 7 June 2020

Micceri, T.: The unicorn, the normal curve, and other improbable creatures. Psychol. Bull. **105**(1), 156–166 (1989). https://doi.org/10.1037/0033-2909.105.1.156

Ministry of Internal Affairs and Communications: 2015 population census. http://www.stat.go.jp/data/kokusei/2015/kekka.html (2017). Accessed 26 July 2018

Ministry of Land, Infrastructure, Transport and Tourism: Cost-effectiveness analysis manual for railway project. Japan Institution of Transport Policy Study, Tokyo (1999)

Ministry of Land, Infrastructure, Transport and Tourism: The methods of evaluating railway projects. http://www.mlit.go.jp/common/000220828.pdf (2012). Accessed 26 July 2018

Ministry of Land, Infrastructure, Transport and Tourism: The report of urban transportation census 2015. http://www.mlit.go.jp/common/001179760.pdf (2017). Accessed 26 July 2018

Ministry of Land, Infrastructure, Transport and Tourism: The number of routes with a congestion rate exceeding 180% in the Tokyo area decreases from 12 to 11: results of an investigation of congestion rate of city railways. http://www.mlit.go.jp/report/press/tetsudo04_hh_000068.html (2018). Accessed 26 July 2018

Mohd Mahudin, N.D., Cox, T., Griffiths, A.: Modelling the spillover effects of rail passenger crowding on individual well being and organisational behaviour. WIT Trans. Built Environ. **116**, 227–238 (2011). https://doi.org/10.2495/UT110201

Mohd Mahudin, N.D., Cox, T., Griffiths, A.: Measuring rail passenger crowding: scale development and psychometric properties. Transp. Res. Part F Traffic Psychol. Behav. **15**(1), 38–51 (2012). https://doi.org/10.1016/j.trf.2011.11.006

Prud'homme, R., Koning, M., Lenormand, L., Fehr, A.: Public transport congestion costs: the case of the Paris subway. Transp. Policy **21**, 101–109 (2012). https://doi.org/10.1016/j.tranpol.2011.11.002

Satorra, A.: Robustness issues in structural equation modeling: a review of recent developments. Qual. Quant. **24**(4), 367–386 (1990). https://doi.org/10.1007/BF00152011

Stutzer, A.: The role of income aspirations in individual happiness. J. Econ. Behav. Organ. **54**(1), 89–109 (2004). https://doi.org/10.1016/j.jebo.2003.04.003

Stutzer, A., Frey, B.S.: Stress that doesn't pay: The commuting paradox. Scand. J. Econ. **110**(2), 339–366 (2008). https://doi.org/10.1111/j.1467-9442.2008.00542.x

Surwit, R.S., Van Tilburg, M.A.L., Zucker, N., McCaskill, C.C., Parekh, P., Feinglos, M.N., Edwards, C.L., Williams, P., Lane, J.D.: Stress management improves long-term glycemic control in type 2 diabetes. Diabetes Care **25**(1), 30–34 (2002). https://doi.org/10.2337/diacare.25.1.30

Tirachini, A., Hensher, D.A., Rose, J.M.: Crowding in public transport systems: Effects on users, operation and implications for the estimation of demand. Transp. Res. Part A Policy Pract. **53**, 36–52 (2013). https://doi.org/10.1016/j.tra.2013.06.005

Tirachini, A., Hensher, D.A., Rose, J.M.: Multimodal pricing and optimal design of urban public transport: the interplay between traffic congestion and bus crowding. Transp. Res. Part B Methodol. **61**, 33–54 (2014). https://doi.org/10.1016/j.trb.2014.01.003

Tirachini, A., Hurtubia, R., Dekker, T., Daziano, R.A.: Estimation of crowding discomfort in public transport: results from Santiago de Chile. Transp. Res. Part A Policy Pract. **103**, 311–326 (2017). https://doi.org/10.1016/j.tra.2017.06.008

Tirachini, A., Sun, L., Erath, A., Chakirov, A.: Valuation of sitting and standing in metro trains using revealed preferences. Transp. Policy **47**, 94–104 (2016). https://doi.org/10.1016/j.tranpol.2015.12.004

Tokyo Metropolitan Government:. Tokyo statistical yearbook 2016. http://www.toukei.metro.tokyo.jp/tnenkan/2016/tn16q3i014.htm (2016). Accessed 26 July 2018

Tokyo Metropolitan Government: Trend in the number of users of the Toei Subway. https://stopcovid19.metro.tokyo.lg.jp/cards/predicted-number-of-toei-subway-passengers/ (2020). Accessed 7 June 2020

Torres, S.J., Nowson, C.A.: Relationship between stress, eating behavior, and obesity. Nutrition **23**(11–12), 887–894 (2007). https://doi.org/10.1016/j.nut.2007.08.008

Wardman, M.: Public transport values of time. Transp. Policy **11**(4), 363–377 (2004). https://doi.org/10.1016/j.tranpol.2004.05.001

Wardman, M., Lyons, G.: The digital revolution and worthwhile use of travel time: implications for appraisal and forecasting. Transportation **43**, 507–530 (2016). https://doi.org/10.1007/s11116-015-9587-0

Wardman, M., Whelan, G.: Twenty years of rail crowding valuation studies: Evidence and lessons from British experience. Transp. Rev. **31**(3), 379–398 (2011). https://doi.org/10.1080/01441647.2010.519127

Whelan, G. A., Crockett, J.: An investigation of the willingness to pay to reduce rail overcrowding. In: First International Conference on Choice Modelling. http://www.icmconference.org.uk/index.php/icmc/icmc2009/paper/view/31 (2009). Accessed 26 July 2018

Wooldridge, J.M.: Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge (2010)

Wright, R.J., Rodriguez, M., Cohen, S.: Review of psychosocial stress and asthma: An integrated biopsychosocial approach. Thorax **53**(12), 1066–1074 (1998)

Ye, R., Titheridge, H.: Satisfaction with the commute: the role of travel mode choice, built environment and attitudes. Transp. Res. Part D Transp. Environ. **52**, 535–547 (2017). https://doi.org/10.1016/j.trd.2016.06.011

You, H.: Agricultural landscape dynamics in response to economic transition: comparisons between different spatial planning zones in Ningbo region, China. Land Use Policy **61**, 316–328 (2017). https://doi.org/10.1016/j.landusepol.2016.11.025

YouGov: COVID-19 fears. https://yougov.co.uk/topics/international/articles-reports/2020/03/17/fear-catching-covid-19 (2020). Accessed 21 May 2020

Zhang, K., Batterman, S., Dion, F.: Vehicle emissions in congestion: comparison of work zone, rush hour and free-flow conditions. Atmos. Environ. **45**(11), 1929–1939 (2011). https://doi.org/10.1016/j.atmosenv.2011.01.030



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