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Time use and spatial influence on transport-related social exclusion, and mental and social health

Dimas B.E. Dharmowijoyo[a,c,*], Yusak O. Susilo[b], Ibnu Syabri[c]

[a] Department of Civil and Environmental Engineering, Institute of Transport and Infrastructure, Universiti Teknologi PETRONAS, 32610 Seri Iskandar, Perak Darul Ridzuan, Malaysia

[b] University of Natural Resources and Life Sciences, Department of Landscape, Spatial and Infrastructure Science, Institute for Transport Studies, Peter-Jordan-Strasse, 82 1190 Vienna, Austria

[c] Urban and Regional Planning Study Programme, School of Architecture, Planning and Policy Development, Institut Teknologi Bandung Labtek IX.A Building Sugijanto Soegijoko, Floor II, ITB, Jalan Ganesha 10, Bandung 40132, Indonesia

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ABSTRACT

Using a modified three-level modelling method and a multidimensional three-week household time-use and activity diary, this study investigates the interaction of the time duration of individuals' activities, travel parameters, the built environment and socio-demographics on people's transport-related social inclusion. Such interactions are assumed to affect one's social and mental health on a daily basis, in particular in developing countries where working conditions, time pressures and income and accessibility gaps are much more extreme than in developed countries. The results show that, in developing countries such as Indonesia, even though people believe that they are well integrated within society, have adequate access to various public amenities, have abundant opportunities for varied social participation and more access to various public amenities, many still have mental health problems due to the existence of physical health problems, chronic diseases, the feeling of insecurity resulting from financial burdens and a lack of social security. Having more inclusive transport access, on the other hand, helps people to have better social health. The life stages of individuals, particularly for those who belong to the later stage, correlates with the probability of having mental and social health problems intensified by a worsened financial status and one's need to work for a longer time. Having more predictable activity–travel patterns and an opportunity for a break from regular work activities during the weekend positively correlates with older people's transport-related social inclusion and positive mental health conditions. More cycling and walking, and the provision of denser public amenities, can contribute to more inclusive transport access and subsequently to one's social and mental health. Moreover, providing a dedicated public transport system for people who reside in Greater Bandung Metropolitan Area is expected to be associated with better transport-related social inclusion and social health.

1. Introduction

Access to essential goods and basic amenities, such as education, health, food, shelter and social security, is fundamental for an individual to live a full and active life. Social exclusion occurs when an individual or a group of individuals is excluded from society for multiple reasons. There is a strong consensus that the structural-economic and socio-cultural dimensions are defined as two separate dimensions of someone's social exclusion (e.g., Kenyon et al., 2002; Levitas, 2006; Delbosc and Currie, 2011; Lucas, 2012; Vrooman and Hoff, 2013). The structural-economic dimension emphasises the limitations of having lower income than average and less adequate access to basic amenities, whereas the socio-cultural dimension refers to how individuals have limited social participation and normative integration into society. Many studies from the domain of transport geography have argued that social exclusion is a process rather than a phrase (Kenyon et al., 2002; Preston and Rajé, 2007; Lucas, 2012; Lucas et al., 2016). From that definition, the structural-economic dimension can describe the process of how people's economic and social characteristics can limit access to various public amenities and to social participation, thus contributing to his/her social-cultural problems and social exclusion.

Many studies in the field of transport geography and travel behaviour have found that someone with low income is more likely to have lower access to motorised modes of transport in Australia (Hurni,

* Corresponding author.
E-mail addresses: dimas.bayu@utp.edu.my (D.B.E. Dharmowijoyo), yusak.susilo@boku.ac.at (Y.O. Susilo).

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2006), the United Kingdom (Lucas, 2012; Department for Transport, 2014; Mackett and Thoreau, 2015), the United States and Canada (Clifton and Lucas, 2004; Morris, 2004; Paez et al., 2010), South Africa (Lucas, 2011), South America (Hernandez and Titheridge, 2016; Blanco and Apaolaza, 2018), and Turkey (Özkazanç and Sönmez, 2017). These people also tend to have poor access to public transport networks due to limited resources to buy public transport tickets and/or a residence in areas with limited access to public transport networks (Dodson et al., 2006; Hurni, 2007; Currie and Delbosc, 2010; Xiao et al., 2017; Pereira et al., 2019). These explanations show that low income can also correspond to transport disadvantages. The combination of income limitation and transport disadvantages can exacerbate the difficulties in out-of-home social participation and access to various public amenities in a geographical manner (Kenyon et al., 2002; Preston and Rajé, 2007; Lucas, 2012; Lucas et al., 2016). The inclusion of other variables in the social dimension, such as accommodation type and educational background, will also classify people as having either more or fewer problems in social exclusion (Lucas, 2012; Mackett and Thoreau, 2015; Lucas et al., 2016).

From the time–space prism perspective, social and transport disadvantages are defined as the provision of 'resources' in the social and transport dimensions that can justify the process of exclusion from society. A lack of resources in the social and transport dimensions can correlate with accessibility poverty in various public amenities (Lucas et al., 2016; Martens, 2016; Pereira et al., 2019). In addition, mobility poverty (such as fewer trips and trip chains and shorter total travel time) and fewer discretionary trips, including for social participation and visiting public amenities (Delbosc and Currie, 2011; Paez et al., 2010; Department for Transport: National Travel Survey. Available from (https://www.gov.uk/government/collections/national-travel-survey-statistics›, 2014; Mackett and Thoreau, 2015; Dharmowijoyo et al., 2016a; Hernandez and Titheridge, 2016; Özkazanç and Sönmez, 2017; Hafezi et al., 2017a, 2018; Daisy et al., 2018a,b) can correlate with limited access to social participation in general (Lucas et al., 2016). Preston and Rajé (2007), Lucas (2012). Lucas et al. (2016) argued that the accessibility and mobility poverty dimensions are the result of the process of social and transport disadvantages. Accessibility and mobility deficiencies are then combined with the perception of good integration in society and the perception of adequate public amenities in a non-geographical respect to explain transport-related social exclusion. To the same extent, the definition of transport-related social exclusion also covers the transport justice definition in which deprivation of opportunities/access due to social and transport aspects, including where people reside shape people's life opportunities (Martens et al., 2012; Martens, 2016). Previous studies have introduced the inclusion of transport disadvantages in the definition of transport-related social exclusion (Kenyon et al., 2002; Preston and Rajé, 2007; Lucas, 2012; Lucas et al., 2016). But previous studies have rarely included empirical data that considers the transport disadvantage dimension in the definition of social exclusion.

Someone with specific social and transport characteristics might work long hours due, in part, to low-skilled labour (Paez et al., 2010; Manoj and Verma, 2015; Dharmowijoyo et al., 2016b, 2018), might undertake a longer time for in-home discretionary activities due to having limited resources, and might travel long hours due to accessibility poverty (Paez et al., 2010; Mackett and Thoreau, 2015; Xiao et al., 2017; Özkazanç and Sönmez, 2017; Allahviranloo and Aissaoui, 2019; Hafezi et al., 2017b; Millward et al., 2019). Undertaking long work hours and commuting/travelling long hours can reduce people's participation in flexible activities, such as out-of-home social participation (Hägerstrand, 1970; Susilo and Kitamura, 2005; Susilo and Dijst, 2009; Kang and Scott, 2010; Dharmowijoyo et al., 2016b, 2018; Allahviranloo and Aissaoui, 2019; Hafezi et al., 2017b; Millward et al., 2019). The time-use dimension can reveal how time poverty can describe transport-related social exclusion. The effect of the time-use dimension in social exclusion has been raised in some previous studies (e.g., Priya Uteng, 2009; Lucas, 2012); however, to the authors' knowledge, the inclusion of time-use dimensions in transport-related social inclusion has rarely used empirical data. Using multiple-day data, time-use studies also reveal the influence of the degree of variability of the undertaken activities and trips among days (Joh et al., 2002; Moiseeva et al., 2014; Allahviranloo and Aissaoui, 2019; Hafezi et al., 2017b; Millward et al., 2019), which can provide another dimension of the time–space prism perspective in explaining transport-related social exclusion. There have also been few previous studies that have included a multi-day analysis framework. A day-to-day variability framework will capture a better picture of how people undertake various activities and the duration of the activities within various weekdays and between weekdays and weekends, in turn reducing bias in explaining transport-related social exclusion/inclusion. The degree of this variability might provide another angle in explaining the influence of a multi-day analysis on transport-related social exclusion.

In addition, spatiotemporal and health variables seem to influence each other (Zhang, 2013; Dharmowijoyo et al., 2015; Wee and Ettema, 2016) which creates endogeneity problems in linear regression models. Some studies—mostly in developed countries—have revealed a theory to link social exclusion with social and mental health (Boniface et al., 2015; Mackett and Thoreau, 2015), whereas some empirical studies have used limited definitions of social exclusion, such as social support (Scanlan et al., 2010), solitary/informal activities and loneliness (Shergold, 2019) and neighbourhood conditions (Tajalli and Hajbabaie, 2017) in explaining mental health. Transport-related social exclusion can comprise the meaning of loneliness, solitary and informal activities, social support, and residence in a better neighbourhood. Due to the definition and its link with the time–space prism concept, transport-related social exclusion can carry time–space information. Therefore, transport-related social inclusion is hypothesised to mediate the relationship between spatiotemporal variables (represented by time-use and activity participation, the degree of variability of the undertaken activities among days and socio-demographic and spatial variables) and

social and mental health, thus solving endogeneity problems.

This study examines the influence of spatiotemporal variables on transport-related social exclusion/inclusion, in turn investigating the interaction of the endogenous transport-related social exclusion/inclusion and spatiotemporal variables on social and mental health. Geographical variables are also part spatiotemporal variables that are assumed to interact with the time-use dimension in affecting transport-related social inclusion/exclusion and, in turn, social and mental health. Some hypotheses can be raised, such as that the types of activities and their duration and/or the degree of variability of the performed activities among days, can significantly correlate with transport-related social exclusion. Another hypothesis can be raised that the different types of travel modes can have different effects on transport-related social inclusion, and endogenous transport-related social inclusion is hypothesised to positively correlate with social and mental health. Moreover, each individual also retains specific needs, constraints, and resources due, in part, to the specific stage of life as represented by age, household size, and number of dependent children, and this can be hypothesised to explain the degree of transport-related social exclusion/inclusion (Lucas, 2004, 2012; Vrooman and Hoff, 2013) and, in turn, social and mental health (Musselwhite and Haddad, 2010; Shergold, 2019). This study utilises the three-level modelling that includes variations in individuals' and other household members' daily activity and travel. Other household members' activity and travel patterns can include the effects of social networks on transport-related social exclusion. Moreover, the three-level modelling is modified to enable the model to solve endogeneity problems that arise from the relationship between spatiotemporal and health variables. This study also uses a multidimensional three-week household time-use and activity diary collected in Bandung, Indonesia. To the authors' knowledge, the majority of social exclusion studies have taken place in developed countries (Church et al., 2000; Schönfelder and Axhausen, 2003; Currie and Delbosc, 2010; Lucas, 2012; Vrooman and Hoff, 2013). With a different angle, social exclusion might also be used to tackle inequality problems, particularly due to economic reasons, in developing countries. Research on the time–space prism and health, particularly in investigating the impact of the time–space prism on social and mental health, is also rarely conducted in developing countries.

In the next section, the data sets and variable specifications will be described. Section 3 presents the descriptive analyses of individuals' day-to-day variability in discretionary activity during the observed period. Sections 4 and 5 describe the proposed model structure and model estimation results, respectively. Conclusions are presented in Section 6.

2. 2013 Bandung metropolitan area data set

The Bandung Metropolitan Area (BMA) data set was collected in 2013. It contained numerical information on individuals' time use and activity participation collected for 21 consecutive days in conjunction with other multidimensional information, such as household type, physical activity and lifestyle, social and family engagements, mental and social health conditions, individuals' subjective characteristics, and subjective well-being data. The data used the household as a unit and contained 191 households totalling 732 individuals. The data was collected with stratified random selection and represents 0.02% of the BMA population in 2013 (Dharmowijoyo et al., 2015, 2017). The sample profile of all 732 individuals is shown in Table 1. For this study, we included only 584 individuals, omitting the data on dependent children.

The household data section included the personal information of household members, household information, perceived measurement of accessibility, and neighbourhood questions. Perceived accessibility was used rather than an objective accessibility measurement due to unpredictable and highly congested traffic conditions and the ever-changing land use development in the BMA that is difficult to be documented well (Susilo et al., 2010; Dharmowijoyo et al., 2018). The household data also contained social participation information, such as how many days on average within a week, and how many hours in a day, individuals undertook social and family interactions. In this study, the density information was used as built environment information; it was obtained from digital land use data provided by Bappeda Kota Bandung (2013).

The data captured 23 types of in-home and out-of-home activity categorisations. Activities were categorised as mandatory (difficult to reschedule, such as work, school, and pick-up/drop-off activities) or discretionary (easy to reschedule, such as leisure and maintenance activities) (Schwanen et al., 2008). Maintenance activities were activities that satisfy household and personal physiological and biological needs (Akar et al., 2011), whereas those undertaken for cultural and psychological reasons were defined as leisure activities (Akar et al., 2011). More complete information regarding the classification of activities can be found in a paper by Dharmowijoyo et al. (2015).

This data set also included multitasking activities, which combined passive leisure (entertainment and socialising) as a secondary activity with various primary activities. Multitasking activities were defined as concurrent activities that contain primary and secondary activities (Circella et al., 2012) for satisfying different needs and desires at the same time.

The questionnaire contained a section with health-related quality of life (QoL) questions and their potential influencing factors. Health-related QoL was developed based on SF-36 (Short-Form 36), one of the most widely used generic measures for health-related surveys. This set of questions has been adopted by more than 11 countries (Zhang, 2013). It contained eight subscales that consider physical, social and mental health which were measured in categories such as physical functioning (PF), limitations on role functioning according to physical health (RP), bodily pain (BP), general health (GH), mental health (MH), limitations on role functioning due to emotional problems (RE), social functioning (SF) and vitality (VT). As suggested by Suzukamo et al. (2011), PF, RP and BP were defined as physical health; RP, SF and RE as social health; and BP, GH, VT, SF and MH as mental health.

Table 1
Profile of the all respondents (732 individuals).

Variables	Percentage or Mean
Socio-demographic characteristics at individual level:	
Male	52.10%
Worker and non-worker	43.64% and 31.05%[1]
Is a dependent child (< = 14 years old)	12.73%
Young adult (Aged 15–22 years old)	18.60%[1]
Aged 23–45 and 45–55 years old	44.76% and 14.27%[1,4]
Part of low income (< IDR 3 million/month) and medium income households (IDR 3–6 million/month)	75.20% and 15.80%[1]
Household characteristics:	
Number of household members	4.52
Number of dependent children per household	0.83
Number of motorised vehicles per household	1.77
Reside within the inner city boundary of BMA and within Greater BMA	44.90% and 37.90%[1]
Trips engagements and travel time spent on weekdays (weekends) [2]*:*	
Number of trips	2.64 (2.29)
Number of trip chains	1.26 (1.08)
Percentage travel time of using motorised mode	39.19% (36.77%)
Percentage travel time of using public transport	14.88% (9.55%)
Percentage travel time of using non-motorised mode	34.49% (32.08%)
Total travel time spent from Monday-Friday (minutes)	74.87(69.35)
Time spent for different activities on weekdays (weekends) [2]*:*	
Time spent for in-home mandatory activities (minutes)	693.17 (738.18)
Time spent for in-home leisure & maintenance activities (minutes)	308.23 (363.09)
Time spent for working/school activities (minutes)	298.85 (161.99)
Time spent for out-of-home grocery shopping (minutes)	13.11 (21.62)
Time spent for out-of-home social-recreational (minutes)	51.72 (61.52)
Time spent for out-of-home other maintenance and sport (minutes)	5.04 (24.75)
Percentage of time engaging with multitasking activities within certain activity on weekdays (weekends) [2]	
Percentage of time engaging with multitasking activities within travel activities	6.89% (5.22%)
Percentage of time engaging with multitasking activities within out-of-home mandatory activities	7.11% (3.64%)
Percentage of time engaging with multitasking activities within out-of-home discretionary activities	17.84% (11.85%)
Built environment variables[3]*:*	
Km-length of road and railway per square-km within the respondents' residential location	38.57 and 4.83
Density of industrial and trade centre/supermall area per square-km within the respondents' residential location	0.024 and 0.005
Density of government office and settlement area per square-km within the respondents' residential location	0.012 and 0.484
Perceived accessibility variables	
Perceived number of public transport lanes passing respondent's resident	2.57
Perceived travel time to CBD and shopping centre area (minutes)	31.27 and 15.85
Perceived travel time to grocery store and park (minutes)	8.34 and 18.29
Perceived travel time to the nearest place to stop public transport (minutes)	14.50
Subjective neighbourhood questions	
Agree to perceive that you have good neighbours and reside in friendly and peace neighbourhood?	3.87
Agree to perceive to have adequate access to good basic social right facilities in your neighbourhood in term of health, education, social-community, and shopping facilities)?	3.50
Agree to perceive to stay in a neighbourhood with good infrastructure, parking space and sanitation?	3.41
Agree perceive that your neighbourhood has good traffic condition?	3.26
Involvement of social and political, and family participation	3.26
How many days in average within a week, individuals spend time for social and political activities with their community/society? (days)	3.26
How long in average individuals spend social and political participation during a day?	3.53
The average variability in individuals' activity-travel patterns on particular days compared to other days	51.23
Transport-related social inclusion index	0.00

[1] The remaining is students (25.31%), part of high-income households (8.90%) and reside within CBD of BMA (17.20%)
[2] The values in brackets show the percentage/mean values on weekends, otherwise is on weekdays
[3] The density is the percentage of a particular type of land use (e.g. industry area or settlement area) in a sub-district in BMA area. The density is calculated based on built area in only horizontal plane in km^2 divided by total area in km^2. The measurement is excluded the area on vertical plane.
[4] Both groups represent groups with different time and space constraints which may have different working quality level and time allocation (Skirbekk, 2003) and different activity-travel patterns in Indonesia context (Dharmowijoyo et al., 2016a).

The survey also included a global subjective well-being (GSWB) variable that contained cognitive and affective aspects of subjective well-being (Diener, 2009; De Vos et al., 2013). The question related to the affective component was '*How do you feel about your life in general?*' which was answered by respondents in four affective dimensions on a 7-point Likert scale from negative to positive expressions. The four affective dimensions were defined as valence and activation along with two combinations of emotions in different positions between the valence and activation dimensions (Russell, 2003; Ettema et al., 2010; De Vos et al., 2013; Schwanen and Wang, 2014). The range of negative to positive expressions of each dimension is presented in Fig. 1. The Satisfaction with Life Scale (SWLS; Diener and Sandvik, 1991; Friman et al., 2017) was used to define the cognitive domain of subjective well-being. The questions used are also presented in Fig. 1.

Fig. 2 exhibits how transport-related social inclusion/exclusion was formulated. The formulation was inspired from Lucas (2012) and further modified based on the variables used in this study. In this research, having a low/high opportunity to access various public amenities can also be represented by the perceived travel time from people's residences to various basic public amenities, whereas having low social participation was assumed to use travel or mobility parameters such as number of trips, trip chains, and total travel time, as argued by previous studies (e.g., Lucas et al., 2016). Variables that captured '*how many days in a week and how many hours in a day someone will spend undertaking social and political activities*' was also used to indicate high or low social participation. In the BMA data, the individuals' perceptions of whether

they have adequate access (in terms of non-physical access) to basic social facilities and good infrastructure, sanitation, and parking spaces can represent whether individuals attain adequate/inadequate access to basic social rights as defined by Church (2000), Kenyon et al. (2002), Lucas (2012) and Vrooman and Hoff (2013). In the data set, there is a question that can represent the lack of normative integration, which was: '*Do you perceive that you have good neighbours and reside in a friendly and peaceful neighbourhood*?' The question contained answers based on a 7-point Likert scale, ranging from totally disagree to totally agree.

The transport-related social inclusion and global subjective well-being index were obtained from factor scores with a varimax rotation of all questions related to these issues, using a basic principal component analysis with a single-factor solution. Factor score is a common method of uncovering latent variables (such as transport-related social inclusion and GSWB), which have multidimensional interpretations (DiStefano et al., 2009). Varimax rotation is commonly used when there is only one factor expected from the interaction of multidimensional information of the latent variables (DiStefano et al., 2009). The factor scores are standardised variables as a Z score metric with a mean of zero and a value range from −3 to 3 across the sample, which essentially carries the same information in a more compact form (Hair et al., 1998; Anable, 2005). SPSS version 20 was used to create factor scores with the least square method. The regression scores aim to find the value Y which minimises the ε in Equation (2) based on the values of the observed variables (X). The regression score is determined by a multivariate procedure that takes into account the correlation among the estimated factors; between the estimated factors and observed variables; and among observed variables.

$$x_i = \mu_i + \sum_{j=1}^{m} \beta_{i,j} y_j + \varepsilon_i \tag{1}$$

$$X = \mu + \beta Y + \varepsilon \tag{2}$$

The factor scores also produce factor loadings of multidimensional information which show the interrelationships among variances of multidimensional information to transport-related social inclusion and the GSWB index. Figs. 1 and 2 show the factor loadings that shape factor scores of the GSWB and the social inclusion index. Lower negative scores indicate a higher risk of low GSWB and social excluded.

3. Day-to-day variability in individuals' and other household members' activity-travel behaviours

Fig. 3 exhibits the relationship between individuals' and other household members' daily work and out-of-home discretionary activity time use by different transport-related social inclusion and social and mental health conditions. Moreover, the effect of stage of life variables, such as socio-demographic variables, and GSWB on transport-related social inclusion and health variables are explored in Fig. 4. In these graphs, 'high transport-related social inclusion, GSWB, and social and mental health' refers to someone with an above-zero (greater than 0) transport-related social inclusion, GSWB, and social and mental health index, whereas 'low transport-related social inclusion, GSWB and social and mental health' means someone with the same as or below zero (≤0) transport-related social inclusion, GSWB and social and mental health index.

Crucially, in this study, people who have better and worse transport-related social inclusion and social and mental health have significantly different activity and travel patterns on a daily basis. People who spend more time working have better transport-related social inclusion and better social and mental health conditions than people who have the opposite arrangement. Working longer hours may indicate someone who has better financial well-being (Shergold, 2019) and a higher level of interaction with others or higher social capital (e.g., Ryff, 1989; Helliwell and Putnam, 2004). As expected, longer time spent in-home and shorter exposure to social time reduces social and mental health

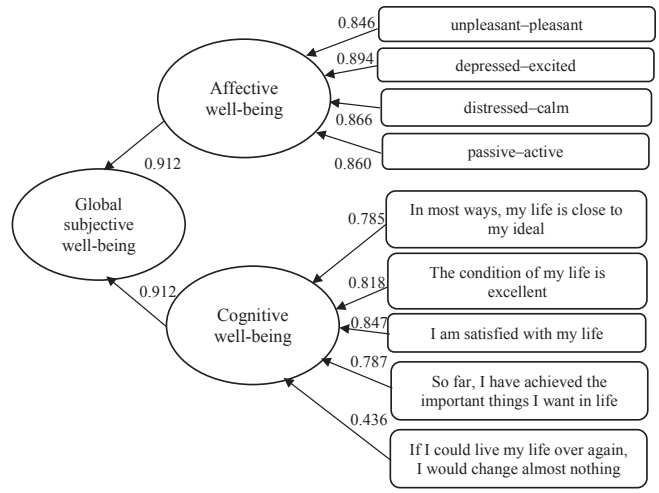


Fig. 1. Measurement model of global subjective well-being.

conditions. The results in Fig. 3 also show that someone with a regular activity-travel pattern on a weekday compared with other weekdays has significantly better social and mental health conditions. This is not the case for transport-related social inclusion.

Those who arrange shorter social activity time from Monday to Saturday, and longer social activity time on Sunday, are socially included, whereas those who have the opposite arrangement are socially excluded. Undertaking social time on Sunday could indicate more meaningful social activity participation than spending social time on weekdays and Saturday, as has been shown to be the case in developed countries (Scanlan et al., 2010).

Fig. 3 also shows how people who live with household members who work longer hours have significantly better transport-related social inclusion and social and mental health conditions than those who live with household members who work shorter hours. However, the difference caused by other household members' out-of-home discretionary time only shows a significant difference for mental health and not for transport-related social inclusion.

In terms of the effect of personal characteristics and GSWB, Fig. 4 shows that males, young persons and people with a high GSWB have better health and transport-related social inclusion conditions than females, older persons and someone with a low GSWB. On the other hand, single and couple households have better health conditions but lower transport-related social inclusion than people with higher household size. As hypothesised, better transport-related social inclusion has a significant positive correlation with health variables.

This section tries to explore how individuals' and other household members' time use may explain why someone is socially included and has better mental and social health. Daily activity-travel participation may provide a more complete picture in terms of capturing people's activity-travel participation with regard to considering a trade-off mechanism between weekdays and weekends; this has been overlooked by studies that captured only one day participation or did not include weekday–weekend observations of activity and travel participation (Susilo and Kitamura, 2005; Kang and Scott, 2010; Moiseeva et al., 2014; Dharmowijoyo et al., 2015, 2017). The variability of individuals' activity-travel participation on multiple weekdays seems to show better results in correspondence with mental health than the configuration of different types of activity on a daily basis. However, this section only provides a bivariate analysis without considering interaction among time and space variables. Therefore, for detailed interaction that includes the complexity among social, spatial, temporal and household dimensions of individuals, an advanced statistical model will be applied in the next section.

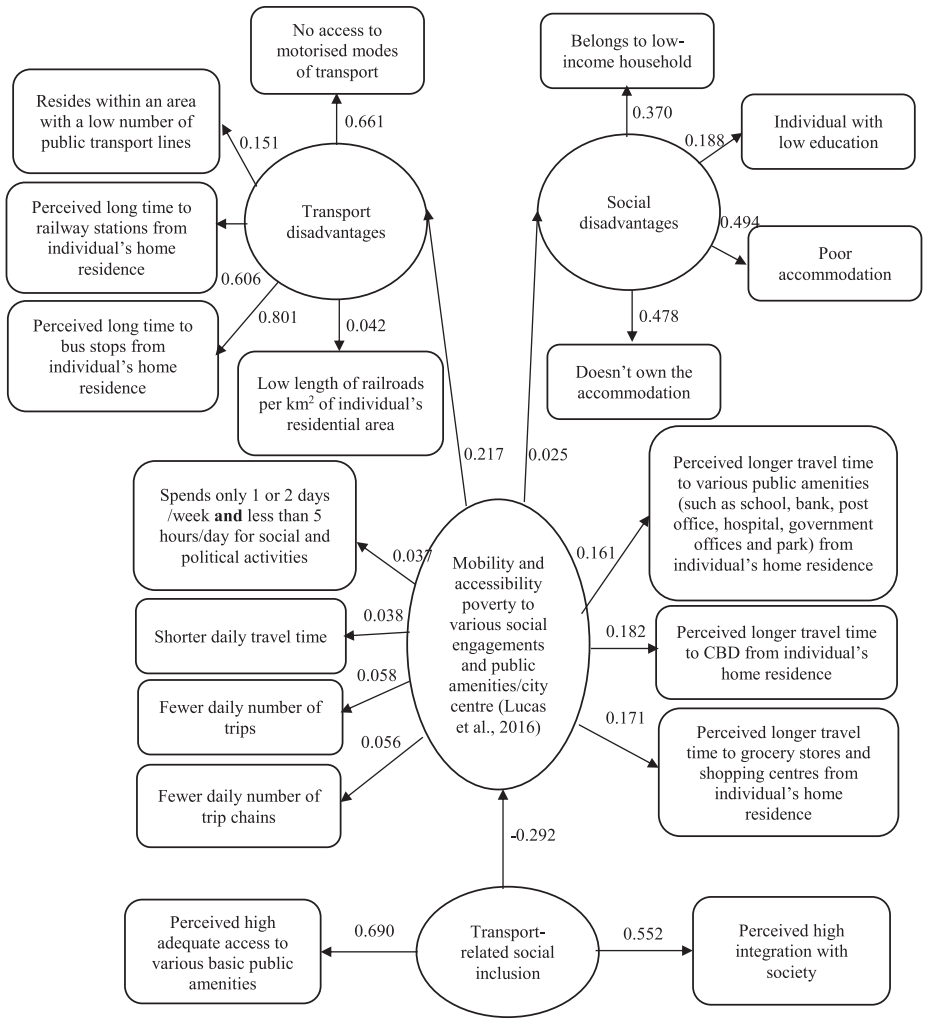


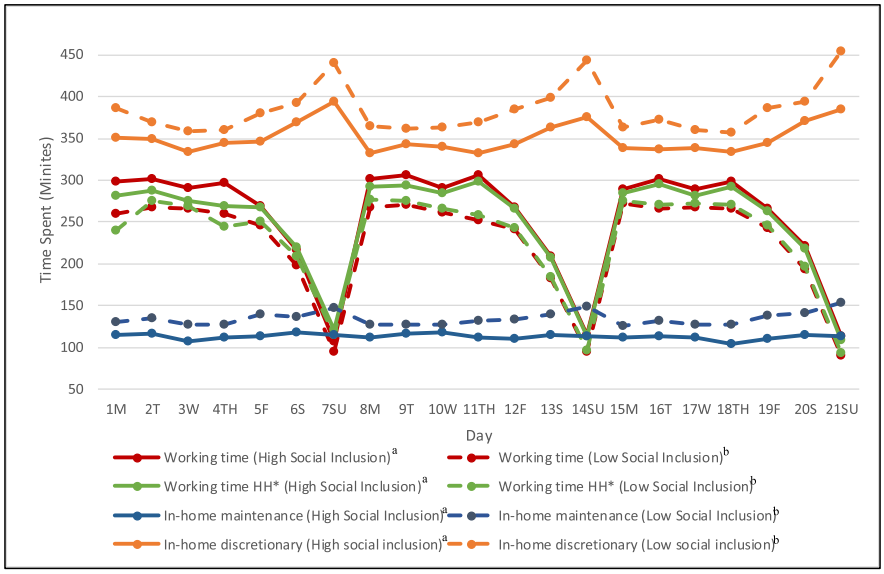
Fig. 2. Factor loadings of the observed variables used to estimate transport-related social inclusion (based on Lucas, 2012; Lucas et al., 2016).

4. Proposed model structure

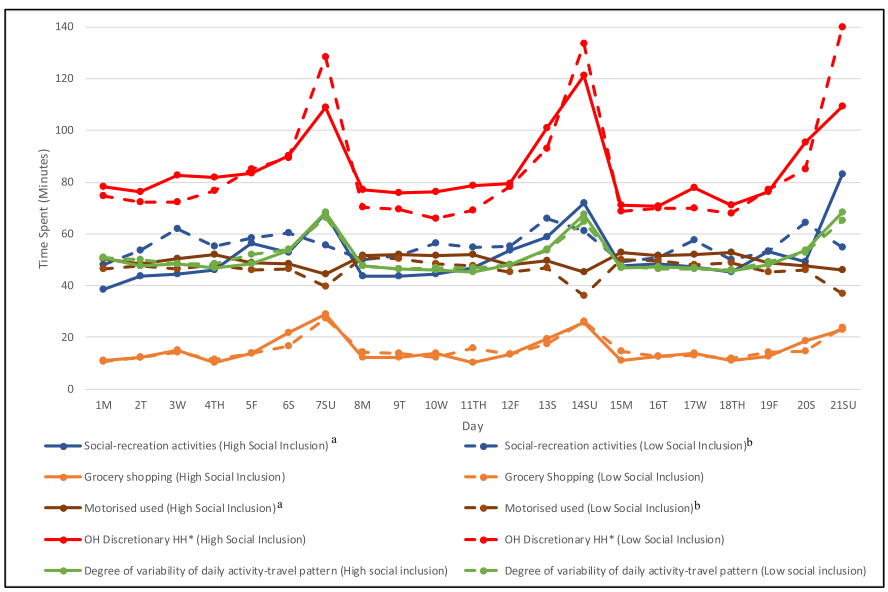
As an extension of the previous section, this section tries to explore the interactions among individuals' personal, household, social, spatial and temporal characteristics on transport-related social inclusion in a multivariate manner. Moreover, the endogenous transport-related social inclusion variable was assumed to interact with spatiotemporal variables (such as time use and activity-travel participation, socio-demographic and spatial variables) on social and mental health in a multivariate manner. Due to the aim of solving the endogeneity problems between spatiotemporal and health variables, transport-related social inclusion was assumed to mediate the relationship, as shown in Fig. 5. In this study, perceived accessibility variables were used to define transport-related social inclusion, thus spatial variables were represented only by the density variables.

Three-level modelling was used in this study. In order to solve endogeneity problems, the three-level modelling was modified to include mechanisms as in three-stage least squares (3SLS) with instrumental variable (IV). IV is a common method to solve endogeneity problems (Garson, 2000; Myung, 2003) and is used as well in creating the initial value of SEM with the Full Information Maximum Likelihood method (SEM with FIML) in LISREL software (Jöreskog and Sörbom, 1996). The creation of estimated transport-related social inclusion ($\overline{transport - relatedsocialinclusion}$) looked like the first stage of 3SLS in creating the IV, whereas the creation of the social and mental health model looked like the second steps of 3SLS. However, the model did not simultaneously run the first and the second stage and omitted the third stage, thus the model did not correlate the error term of the first and the second stage as contrary with 3SLS. Due to the exclusion of the correlation of the error terms of the first and second equations, this model can be defined as a limited information model of Structural Equation Modelling (SEM), whereas 3SLS and SEM with FIML are full information models of SEM (Myung, 2003). In addition to mechanisms to solve endogeneity problems, as original multilevel modelling, the modified three-level modelling included nesting effects of the variability of individuals' and other household members' day-to-day activity-travel behaviour. In social science research, hierarchical nesting observations (such as a day-to-day effect and the variability of other household members' activity-travel participation) should be considered to better capture individuals' behaviour instead of mutually independent observations (Snijders and Bosker, 1999; Schwanen et al., 2008).

The coefficients of parameters (βn) in this model considered the individuals' and other household members' day-to-day activity-travel participation variations made by individual i on day t and part of household h. The uncorrelated household and individual specific error terms (u_h and u_i) had a mean value of zero and a variance of σ_u, while $\varepsilon_{h,i,t}$ was the uncorrelated combined household, individual and time error components with a mean value of zero. The household and individual



(a) Working and in-home activity time pattern on transport-related social inclusion



(b) Out-of-home discretionary time pattern and degree of variability of daily activity-travel pattern on transport-related social inclusion

Fig. 3. Individuals' daily work and in-home and out-of-home discretionary time use by social inclusion and social and mental health index.

specific error terms captured the unobserved heterogeneity amongst households and individuals, respectively. This means that the inclusion of these two effects will better estimate parameters for understanding the relationships among multiple characteristics of individuals within the time–space perspective when explaining social inclusion and social and mental health. Estimating better or non-biased parameters may lead to the recommendation of better policies for solving social exclusion and mental and social health problems. The method was not expected to deal with any reciprocal effect in examining relationships between social inclusion and mental and social health.

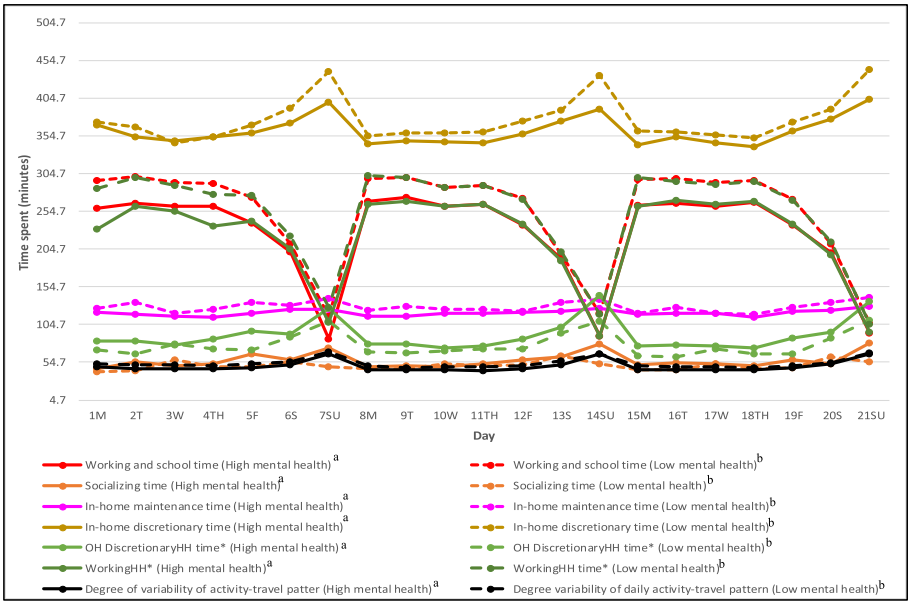
To more clearly explain the model in Fig. 5 using mathematical forms, Equations (3)–(5) are written as follows:

$$(Transport - related\ social\ inclusion)_{h,i}(\alpha_{h,i} + u_h + u_i) + \beta_1 W_{h,i} + \beta_2 R_{h,i} + \beta_3 Time - Act_{h,i,t} + \beta_4 Travel_{h,i,t} + \beta_5 Multitask_{,h,i,t} + \beta_6 OSWB_{h,t} + \alpha_{h,\ i,\ t} \quad (3)$$

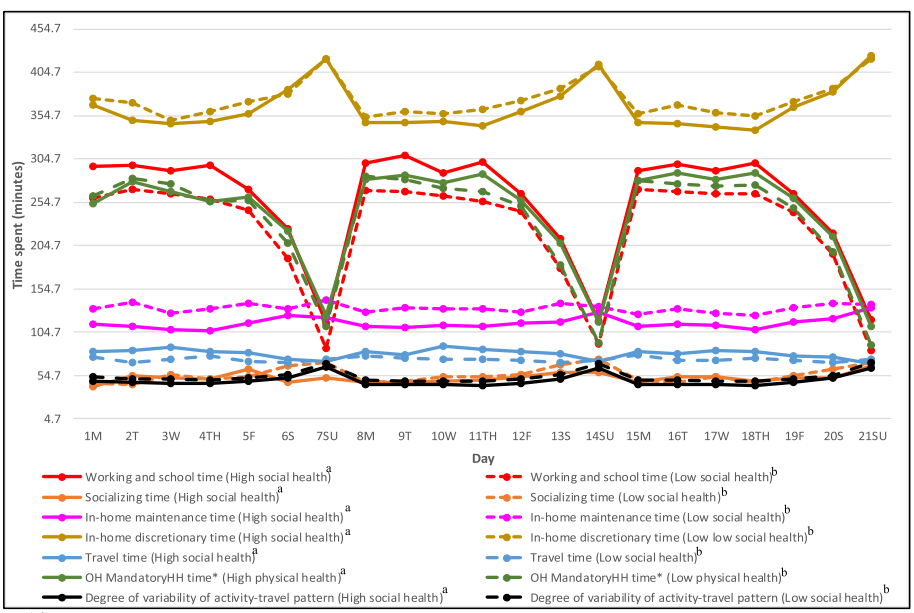
$$(Mentalhealth)_{h,i} = (\alpha_{h,i} + u_h + u_i) + \beta_7 (\widehat{transport - relatedsocialinclusion})_{h,i} + \beta_8 W_{h,i} + \beta_9 R_{h,i} + \beta_{10} Time - Act_{h,i,t} + \beta_{11} Travel_{h,i,t} + \beta_{12} Multitask_{h,i,t} + \beta_{13} GSWB_{h,i} + \varepsilon_{h,i,t} \quad (4)$$

$$(Socialhealth)_{h,i} = (\alpha_{h,i} + u_h + u_i) + \beta_{14} (\widehat{transport - relatedsocialinclusion})_{h,i} + \beta_{15} W_{h,i} + \beta_{16} R_{h,i} + \beta_{17} Time - Act_{h,i,t} + \beta_{18} Travel_{h,i,t} + \beta_{19} Multitask_{h,i,t} + \beta_{20} GSWB_{h,t} + \varepsilon_{h,i,t} \quad (5)$$

Linear and non-linear mixed effect models, or an *NLME* package, was used to apply the modified three-level modelling in this study (Pinheiro et al., 2017). The coefficient parameters in *NLME* were estimated by the maximum likelihood estimator, as generally shown by Equation (3) (Levy, 2010; Pinheiro et al., 2017). The idea of hierarchical nesting was to find parameters $\sum_b$which are shared among



(c) Activity time pattern and degree of variability of daily activity-travel pattern on mental health



(d) Activity time pattern and degree of variability of daily activity-travel pattern on social health

Fig. 3. (*continued*)

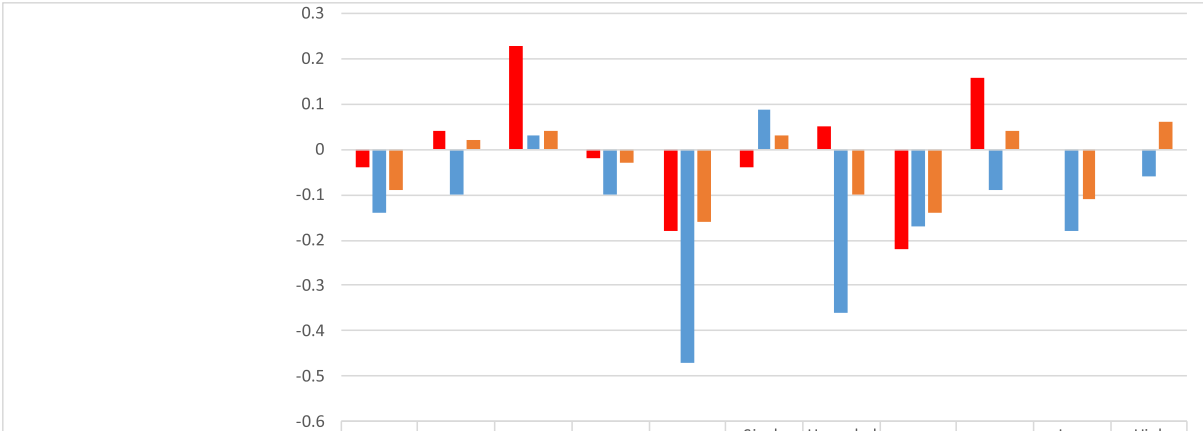
observations within a nested group. The parameter $\sum_b$ was then used to jointly estimate parameter β. This means that regression parameter β is estimated with the inclusion of variations of nested observations.

$$L^*\left(\sum_b, \beta; y\right) = \int (P(y|\beta, b, i)\left(P\left(b\middle|\sum_b\right)\right)db \tag{6}$$

5. Model estimation results

Table 2 shows how personal, household, social, spatial and temporal characteristics of a person explain the degree of transport-related social inclusion and social and mental health conditions. The positive and negative signs show the effect of each independent variable on the dependent variables. The shown estimation result uses standardised variables, thus the magnitude effect among independent variables can be compared. The relationship between the endogenous transport-related social exclusion and social and mental health follow the hypothetical model proposed in Fig. 5. The endogenous transport-related social inclusion variable is negatively and positively associated with mental and social health, respectively. The variances explained by other household members' activity-travel participation are higher in magnitude than the given individuals' day-to-day variation in the transport-related social inclusion and social health model, whereas the opposite result is found for the mental health model. Therefore, in the transport-related social inclusion and social health model, excluding the roles and impacts of other household members' activity-travel patterns can increase the unexplained error term and lead to a higher proportion of bias in the model estimation results. This, consequently, can lead us to create ineffective policies and unwanted outcomes.

From Table 2, the influence of travel and time use and activity participation variables on transport-related social inclusion are found to be significant. Having commitments to travelling with any modes of



	Female	Male	Young persons	People at productive age	Senior citizens	Single and couple household	Household with more than 2 people	Low GSWB	High GSWB	Low transport-related social inclusion	High transport-related social inclusion
Transport-related social inclusion	-0.04[a]	0.04[b]	0.23[2, 3,]	-0.02[1,3]	-0.18[1,2]	-0.04[a]	0.05[b]	-0.22[a]	0.16[b]		
Social health	-0.14[a]	-0.1[b]	0.03[2, 3,]	-0.1[1,3]	-0.47[1,2]	0.09[a]	-0.36[b]	-0.17[a]	-0.09[b]	-0.18[a]	-0.06[b]
Mental Health	-0.09[a]	0.02[b]	0.04[2, 3,]	-0.03[1,3]	-0.16[1,2]	0.03[a]	-0.1[b]	-0.14[a]	0.04[b]	-0.11[a]	0.06[b]

Fig. 4. Socio-demographic and global subjective well-being effect on transport-related social inclusion and health Items in superscript (a, b) indicate that means are significantly different from the opposite group (ANOVA) with p-value < 0.1 Items in superscript (1, 2) indicate that means are significantly different from means of young person and people at productive age group with p-value < 0.1 Items in superscript (1, 3) indicate that means are significantly different from young person and senior citizen group with p-value < 0.1 Items in superscript (2, 3) indicate that means are significantly different from people at productive age and senior citizen group with p-value < 0.1.

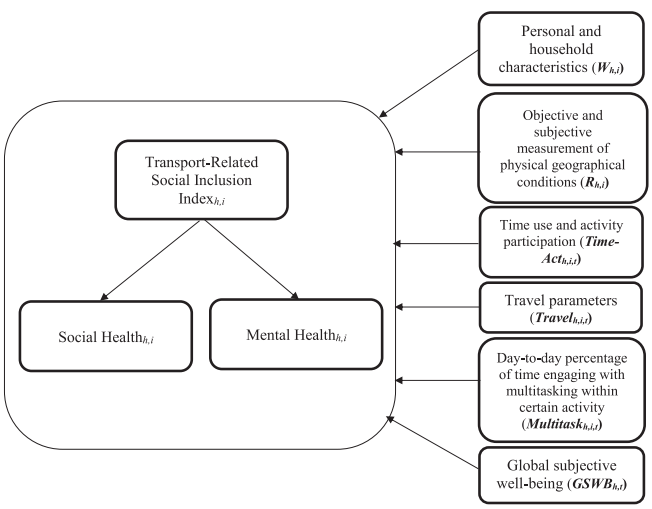


Fig. 5. The proposed model *Note: Exogenous and endogenous variables may be nested by household* (h)*, individual* (i) *or day* (t).

travel shows a positive impact on transport-related social inclusion, whereas performing in-home activities and out-of-home mandatory activities shows the opposite effect. The effect of in-home activities and out-of-home mandatory activities seems to be higher on reducing the transport-related social inclusion index than the effect of out-of-home socialising, maintenance and sport activities. This result shows that an increase of 1% in using non-motorised and motorised modes makes 0.012 and 0.010 positive correlation on transport-related social inclusion, whereas the effect of an increase of 1% in the use of public transport modes only correlates with 0.005 positive effect on transport-related social inclusion. In terms of the effect of activity participation, an increase of one minute duration of out-of-home mandatory, in-home leisure, in-home mandatory and in-home maintenance time makes 0.067, 0.051, 0.049 and 0.047 negative correlation on transport-related social inclusion, respectively. In travel behaviour research, the increased time spent on fixed/mandatory activities (e.g., work/school) and in-home activities can reduce the number of trips/trip chains and travel time (Ettema and Verschuren, 2007; Novaco and Gonzales, 2009; Kang and Scott, 2010; Dharmowijoyo et al., 2016b); therefore, it can reduce the opportunities/access to various social participation. But the effect is much lower for out-of-home discretionary activities (Lu and Pass, 1999; Dharmowijoyo et al., 2016b) due to the flexible nature of the discretionary activities as compared to in-home and out-of-home mandatory activities (Lu and Pas, 1999; Schwanen et al., 2008; Dharmowijoyo et al., 2018).

The degree of variability/regularity in individuals' and other household members' activity-travel patterns and time use across different days of the week are found to be significantly correlated with one's transport-related social inclusion. An increase in one unit of the average variability in individuals' and other household members' activity-travel patterns on a weekday compared to other weekdays makes 0.017 negative correlation on transport-related social inclusion, whereas the effect of the average variability in individuals' activity-travel patterns on a weekend compared to weekdays only makes a very marginal negative correlation on transport-related social inclusion. On social and mental health characteristics, however, what was found to matter is only whether one carries out different activity engagement between the weekend and weekdays—in other words, whether one has a more relaxed schedule of personal enjoyment on the weekend compared to his/her work-oriented weekday schedule. Table 2 shows that an increase in one unit of the average variability in individuals' activity-travel pattern on a weekend compared to weekdays makes 0.001 negative and positive correlation on mental health and social health, respectively.

With the inclusion of transport dimensions, males are found to be more socially excluded than women; this differs from previous results in developed countries without the inclusion of transport dimensions in the definition of social inclusion (Priya Uteng, 2009). Males are found to have less 0.066 of the transport-related social inclusion conditions than females. This difference in finding is due to the inclusion of transport dimensions in social inclusion analysis; that is, men in developing countries have much longer working hours on average than

TABLE 2
Model estimation results for transport-related social inclusion, social and mental health condition (the shown estimation parameters are standardised variables and only significant variables with p value < 0.1 are shown).

Variables	Transport-related Social Inclusion		Mental Health		Social Health	
	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat
Intercept	0.492	2.083	3.994	5.431	2.271	4.878
Personal characteristics						
Male (vs. female)	−0.066	−2.942	−0.203	−2.837		
Workers			−0.500	−6.972	−0.181	−5.306
Students	0.088	12.991	−0.307	−545.464	−0.372	−516.631
Non-workers	Ref	Ref	Ref	Ref	Ref	Ref
Aged < 22	−0.055	−3.252	0.295	2.842	0.393	7.964
Aged 23–45	−0.028	−1.701	0.709	5.738	0.334	5.662
Aged 45–55			−0.453	−4.755		
Age 55+	Ref	Ref	Ref	Ref	Ref	Ref
Household characteristics						
Low-income household			−0.846	−5.399	−0.306	−3.221
Medium-income household			−0.568	−3.415		
High-income household			Ref	Ref		
Number of household members	0.058	3.716	−0.867	−625.140	−0.695	−391.571
Number of dependent children within household	0.090	2.122			0.192	2.770
Individual travel characteristics						
Access to motorised mode					−0.135	−2.013
Percentage using motorised mode	0.010	24.837				
Percentage using public transport mode	0.005	14.960				
Percentage using non-motorised mode	0.012	40.873				
Time-use characteristics						
Time spent for in-home mandatory activities	−0.049	−68.738				
Time spent for in-home maintenance activities	−0.047	−62.994				
Time spent for in-home leisure	−0.051	−68.391				
Time spent for out-of-home mandatory activities	−0.067	−61.138				
Time spent for out-of-home social activities	−0.025	−54.765				
Time spent for grocery shopping	−0.007	−26.035				
Time spent for other out-of-home maintenance activities	−0.009	–32.920				
Time spent for out-of-home sports activities	−0.008	−31.593				
Percentage of time engaging with multitasking activities within travel						
Percentage of time engaging with multitasking activities within in-home mandatory activities						
Percentage of time engaging with multitasking activities within in-home discretionary activities						
Percentage of time engaging with multitasking activities within out-of-home mandatory activities			0.001	3.012	−0.001	−3.032
Percentage of time engaging with multitasking activities within out-of-home discretionary activities	−0.001	−5.110				
The average variability in individuals' and other household members' activity-travel patterns on particular weekdays compared to other weekdays						
The average variability in individuals' activity-travel patterns on particular weekdays compared to other weekdays	−0.017	−3.997				
The average variability in individuals' activity-travel patterns on particular weekends compared to other weekdays	−0.001	−1.681	−0.001	−2.467	0.001	2.474
The average variability in other household members' activity-travel patterns on particular days compared to other days	−0.017	−4.359				
Global subjective well-being	0.066	10.215	−0.836	−1116.621	−0.074	−77.204
Endogenous of transport-related social inclusion			−0.003	4.925	0.004	4.908
Geographic characteristics						
Resident of Greater BMA area (vs. central city)	−0.0715	−16.036	−0.258	−648.956	−0.080	−158.008
Km-length of road/ km^2 within the respondents' residential location						
Population density/km^2 within the respondents' residential location	0.2111	2.796				
Density of settlement area/ km^2 within the respondents' residential location						
Density of trade centre area/ km^2 within the respondents' residential location						
Density of industrial area/ km^2 within the respondents' residential location	−0.276	−3.692	−0.320	−2.320		
Density of agricultural area/ km^2 within the respondents' residential location	0.622	6.496			−0.182	−1.912
Diversity of land use within the respondents' residential location	−0.778	−88.900				
Mean of the dependent variables	0		−0.031		−0.121	
SD	1.000		0.895		0.956	
Household specific error term	1.098		1.214		0.882	
Individual specific error term	0.227		1.393		0.689	
White noise	0.016		0.001		0.001	
AIC	−57702.40		−116388.9		−110156.4	
BIC	−57393.36		−116035.8		−109810.6	
Log likelihood	28893.20		58242.47		55125.21	

Notes: Negative coefficients indicate greater social exclusion, mental and social health problems.

women (Manoj and Verma, 2015; Liu et al., 2018) and, consequently, have much less opportunity to engage in social participation. In the mental health model, males are also found to have a mental health index 0.203 lower than females, whereas no difference is found between males and females in the social health model. Moreover, for workers, having tighter time–space constraints and, for non-workers,

having more flexible time–space constraints (but less social capital due to more in-home activity duration) can worsen the transport-related social inclusion condition of men. In terms of the social and mental health model, financial conditions worsen mental health problems of people who have tighter time–space constraints (such as workers and students), as has also been demonstrated in developed countries (Shergold, 2019). Workers with low- and middle-incomes are found to have less 0.85 and 0.57 of mental health index than workers from high-income households, whereas low-income workers have less 0.31 of social health index than high income workers.

Males over 45 years old correspond with lower mental health than younger males, while males over 55 years old have lower social health conditions. Males 45–55 years old have an additional 1.16 and 0.75 reduction in the mental health index compared to males between 23 and 45 years old and at the youngest age, respectively. Moreover, males and females from senior citizen groups are found to have less 0.33 and 0.39 of the social health index than males and females between 23 and 45 years old and below 22 years old, respectively. This is presumably because males over 55 years old, compared to females and their younger counterparts, have less social contact (Musselwhite and Haddad, 2010; Irish Aid, 2016; Allahviranloo and Aissaoui, 2019; Daisy et al., 2019; Hafezi et al., 2017b; Millward et al., 2019; Shergold, 2019), more problems with physical limitations and chronic diseases (Musselwhite and Haddad, 2010; Irish Aid, 2016; Shergold, 2019) and have more feelings of insecurity that result from a lack of social security systems and the financial burdens in developing countries (Irish Aid, 2016). Feeling tight due to work and study commitments might worsen mental and social health conditions of male workers over 45 years old.

More members in the household may provide more opportunities to have social engagement with family and society and to avoid individuals feeling alone or engaging in solitary activities, as shown as well in developed countries (Shergold, 2019). Some studies, however, have also shown that providing care to an older member of a household and a larger household size are associated with psychological distress and social and mental health problems, whereas providing care to dependent children tends to show the opposite results (Schulz et al., 1977; Donaldson et al., 1998). In line with Schultz et al.'s (1997) and Donaldson et al.'s (1998) studies, a higher household size reduces 0.70 and 0.87 in the social and mental health index, respectively, whereas having more dependent children makes 0.19 improvement in the social health index.

In terms of the impact of opportunities offered by geographical conditions, residing near a city centre and within populated areas positively correlates with transport-related social inclusion. On the other hand, residing in areas with denser industrial activity that are far from a city centre (Redfearn, 2009; Arifwidodo, 2012) shows opposite results. The results also exhibit that residing in denser industrial and agricultural areas increases mental and social health problems, respectively.

6. Conclusion and discussion

This study reveals that, in developing countries, whilst one may perceive him/herself integrated within the community with adequate access to various public amenities and more opportunities for various social activities, that person may still have mental health problems due to physical limitations, chronic diseases, the insecurity resulting from financial burdens and a lack of social security. This is in line with a previous study in Australia, which also showed that a proxy of transport-related social inclusion negatively correlates with mental health indicators (Scanlan et al., 2010).

Older people are more likely to have lower mental and social health conditions but improving their transport-related social inclusion conditions enhances their social health conditions, as shown as well in developed countries (Tajalli and Hajbabaie, 2017; Shergold, 2019). In contrast to results found in developed countries (Musselwhite and Haddad, 2010; Shergold, 2019), social and mental health conditions of older people are worsened by a precarious financial status and feeling tight due to longer working hours.

The presence of a dependent child improves older people's social health conditions, whereas the responsibility to provide care for an older family member has the opposite effect for one's mental and social health, as shown as well in developed countries (Schulz et al., 1977; Donaldson et al., 1998). With the addition of time–space perspectives to the definition of social inclusion, this study shows that spending more time on work/school and in-home activities worsens one's transport-related social inclusion and subsequently worsens that person's social health conditions. Having less variation in one's travel and activity patterns, with a consistent break-up from regular work-related trips and activities on the weekend, positively correlates with one's transport-related social inclusion and mental health conditions. Furthermore, regular engagement in household members' activity-travel patterns across weekdays also helps a person to be socially included, in turn helping to enhance his/her social health. In terms of the effect of modes of transport, more cycling and walking can help in improving transport-related social inclusion, similar to results shown in developed countries (Tajalli and Hajbabaie, 2017). Providing denser public amenities and dedicated public transport lines for the areas that are farther from the city centre can also contribute to more inclusive transport access, and this can directly and indirectly improve social health.

This study overlooked the penetration of information communications technologies that might improve people's transport-related social inclusion and, in turn, their mental and social health. The penetration of communications technologies, including access or lack of access to the internet and activities that use digital technology, can shift the definitions of social inclusion and exclusion. Individuals' activity diaries can provide insight about the expanded definition of social networks and social participation and the influence of online activities on aspects of health. But a lack of social security, the existence of physical limitations and chronic diseases and financial burdens might better explain people's mental health and how their activity and travel patterns are shaped. Greater detail about social engagement, such as religious, family, and hobby-related activities, is also likely to explain the impact of these types of engagement on mental and social health.

CRediT authorship contribution statement

Dimas B.E. Dharmowijoyo: Conceptualization, Data curation, Funding acquisition, Formal analysis, Methodology, Writing - original draft, Writing - review & editing. **Yusak O. Susilo:** Data curation, Formal analysis, Funding acquisition, Methodology, Writing - review & editing. **Ibnu Syabri:** Formal analysis, Funding acquisition, Writing - original draft.

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