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THE INFLUENCE OF TRAVEL MODE CHOICE ON SUBJECTIVE WELL-BEING - A CASE STUDY

Summary. The correlation between mobility and subjective well-being (SWB) has received much attention lately. Previous researchers have studied the effect of health parameters or SWB on transport mode; however, there is a lack of study on the influence of travel mode choice (TMC) for daily activities on SWB. Besides, the prediction of TMC is critical for transport planning. Therefore, the current study aims to study the TMC and its influence on overall SWB. Data from 732 individuals and 191 households are collected using random sampling techniques, which represents 0.029% of the total population. Statistical Package for Social Sciences (SPSS) was used for descriptive statistics, whereas R software was used for the multilevel linear regression analysis. The model estimation results show a significant correlation among the variables ($p < 0.05$, $R^2 > 0.20$). Besides, those who are exposed to public transport and tend to use non-motorized transport modes engage in more physical activities than those who use a private vehicle, which has a negative impact on SWB. The outcome of current research helps policymakers build policies to achieve a sustainable transportation system.

1. INTRODUCTION

Based on the participation or engagement of a diverse set of individuals' daily activities, such activities are categorized as mandatory and discretionary activities and are additionally classified as leisure and maintenance activities. In addition, certain activities are carried out at home and are referred to as in-home (IH) activities, and others are out-of-home (OH) activities [1]. The question arises of why people must travel and use different transport modes for traveling. Traveling is a common aspect of practically everyone's lives [2]. As it is a well-known fact that not all activities take place in the same places, traveling is required to satisfy needs and desires, as well as to participate in various activities. However, travel is also a permanent constraint to engage in different daily activities [3, 4]. People use different transport modes to travel to and engage in activities at diverse locations, as shown in Fig. 1.

The total travel time is subject to the availability of action location, type of action, available travel mode, and individual commitments [5]. It is commonly believed that putting an activity close to where people live and promoting motorized transportation will reduce travel time. Some actions are within walking distance, while others are further away. On the other hand, some people travel for obligatory reasons, while others go for optional, maintenance, and leisure reasons. These journeys are made for both IH and OH activities [6].

The prediction and analysis of travel mode choice (TMC) are vital for better travel demand and transport planning. Analysis of TMC can help in the assessment of changes in travel behaviors, which

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can help practitioners develop the policy and infrastructure that promote a sustainable transportation system [1, 7]. In recent decades, the TMC prediction has received increasing attention for better transport planning and research. Choosing a specific transport mode for certain activities provides substantial environmental, transport-related, and health benefits such as reduced greenhouse gas emissions, traffic congestion, and health-related issues [8]. Besides, several factors affect TMC, such as road safety, weather, built environment, time, cost, household income, location of the activity, availability of cars in a household, infrastructure, and available transport modes. Choosing a specific transport mode to travel and participate in certain activities has a strong correlation with subjective well-being (SWB) [9, 10].

Past studies considered several factors to study TMC using conventional techniques such as regression analysis and multivariate analysis using SPSS. Recently, most researchers have mainly focused on modern techniques such as artificial intelligence (AI), machine learning (ML), deep learning (DL), and reinforcement learning (RL). Several algorithms such as gradient boosting trees (GBT), k-neural networking (k-NN), decision trees (DT), extreme gradient boosting trees (XGBT), random forest (RF), and support vector machine (SVM) are used to study TMC [11-13]. Besides, past studies have investigated the influence of health parameters on TMC. Previous studies are limited to using conventional and modern techniques to predict TMC without considering its effect on health parameters and SWB. Therefore, the current study aims to study the TMC used for several activities and its influence on overall SWB.

Fig. 1. Integration with the Activity-based Model

The major goals of the World Health Organization that have been publicly adopted are increased well-being, happiness, and quality of life. SWB is a conception of well-being that is examined via the prism of a person's views and personal observations. It is frequently divided into hedonic (joy, pleasure, and good thoughts) and eudemonic (finding meaning, principle, or self-actualization) parts [14]. The policymakers aim to study and exercise transportation to improve health parameters and promote sustainable transportation systems, while researchers studied their association to promote SWB in travel. Even though the effects of transport on physical health are fairly deeply understood, significant attention has been placed in the current study on the connection between TMC and SWB. On the other hand, how socio-demographic factors influence the TMC has been thoroughly researched.

Therefore, the current paper aims to study (1) socio-demographic and economic variables, (2) time-use and activity travel participation, (3) TMC used for a set of daily activities, and (4) its influence on SWB. Recent and past studies show that traveling by public transport (PT) is negatively allied with individuals' well-being. However, it has been discovered that engaging in secondary activities (especially offline socializing) when traveling improves individuals' overall well-being and everyday travel experiences. Moreover, PT is a free-space transportation platform that helps people go where they need to go while allowing them to fulfill their needs and demands under constrained time and space limits.

The current study answers the following research questions: Why does an individual choose several transport modes? What is the correlation between TMC and SWB? The following hypotheses are proposed to answer the research questions: There is a positive association between socio-demographic and economic and SWB. Travel mode choice positively influences SWB. The type of activity (such as leisure, mandatory, and maintenance activities) enhances SWB.

2. LITERATURE REVIEW

There have been a number of studies related to TMC, SWB, daily commuting, and the built environment. Some of these studies investigated TMC in childhood for daily commuting to school, while others studied employee ridership. Moreover, recent and past researchers studied commuting to work and school using different transport modes and its influence on mental, social, and physical health parameters and the environment. Besides, past researchers studied the determinants of TMC and concluded that it is affected by socio-demographic and economic factors. Moreover, several studies have investigated the correlation between health parameters and TMC using conventional techniques. In addition, recent studies used modern techniques such as ML, AI, ANN, DL, and RF by utilizing DT, RF, GBT, XGBT, and SVM algorithms to study TMC. A summary of several studies, along with their outcomes, is presented below.

A means of getting to school in the two cities of the Kingdom of Saudi Arabia was investigated by Assi et al. Several input variables were used, including student data such as grade, duration of trip, proximity of home to school, number of students in the household, size of family, income, and parental education level. The output variables were binary, meaning that the choice was between walking or driving a passenger car to school. They concluded that the main factors influencing mode-choice behavior were family income, journey time, and parent education level [15]. In order to determine the impact of a metropolitan type of school TMC, some researchers (e.g., [16]) conducted a study on elementary schools. Sixteen schools in North and South California provided information on their students' travel habits. The study found that a wide range of additional characteristics affect the likelihood of choosing a school mode. Urban form is the most important aspect among them, followed by the safety of the surrounding area, family mobility alternatives, societal values, car safety, and the caregiver's attitude.

Ohta et al. studied the impact of commuting to work and leisure-time physical activities on mental health and concluded that using active transport modes, such as walking or cycling, is connected with better mental health [10]. Besides, Schäfer et al. found that health indicators are associated with daily physical activity and traveling to work with various modes of transportation. They concluded that active commuting offers health benefits comparable to moderate fitness training [17]. Hislop studied the communication behaviors (use of mobile communication technologies) of business travelers to work using a car. He concluded that it is hard for an individual to communicate with clients while using a private vehicle [18].

Susilo and Dijst investigated the correlation between travel time ratio and activity participation and determined that trip time is affected by activity type, location, commitment, and mode of transportation available. They concluded that the trip time ratio is influenced by the home trade-off [19]. Moreover, in a previous study [20], we found that OH commitments are highly affected by the type of activity (either mandatory, leisure, or maintenance activity), individual travel mode (MT, NMT, or PT), and location of activity. Besides, Madhuwanthi et al. studied the determinants of TMC and concluded that vehicle ownership, comfort, income, and safety influence TMC [21].

The eudemonic aspect of SWB is well explained in research [22]. Recently, the transportation research community focused on SWB and its concept, exploring how it influences transport options. For instance, in work [8], we found an influence of travel mode and determinants of well-being on SWB from active transport modes, such as walking and cycling. Singleton used 700 daily commuters' data and concluded that cycling and walking scored significantly higher on hedonic well-being, tests of confidence, mental and physical health, and positive affect. These results point to the potential advantages of physically active commutes. Commuters who ride their bikes, however, recorded greater anxiety and distress and lower security, demonstrating the importance of multi-dimensional travel SWB metrics. Improving the quality of transportation through several means—for example, providing protected infrastructure to make riding a bicycle safer—could have a major positive impact on commuters' well-being. The safety issues related to daily commuters are discussed in detail in other research [23].

Furthermore, in another study, Singleton concluded that there are strong and significant correlations among TMC, SWB, and multitasking activities. With the use of data from 546 commuters, he discovered that while selecting a mode of transportation for a certain activity, travelers may take past experiences and expectations into account in relation to their pleasure and well-being, but that multitasking while traveling may also be more about "killing time" than being productive [24]. However, Hamadneh et al. studied the correlation between multitasking and tools onboard technologies to make some of their trip time more productive in response to Singleton's studies in which he concluded that multitasking in traveling is killing time more than aiding productivity. With a total sample size of 525 individuals, they employed 12 tools carried by travelers in addition to 10 onboard activities. They concluded that the onboard tools positively affect travel time and exhibit a moderate to high correlation [9].

Moreover, Hamadneh et al. studied onboard activities by considering autonomous vehicles and PT and determined that social media has a strong positive effect on TMC, whereas writing has the opposite effect. Besides, shared autonomous vehicles are greatly affected by cost, time, and onboard activities, whereas individuals are more likely to use PT in urban areas to perform multitasking activities [25]. Other research (e.g., [26]) presents the results of the influence of SWB on TMC on a large scale and its application in transportation research. Moreover, both the results of the present and future development of cities and their effect on quality of life can be found in the study presented in [5]. Recent studies have mostly focused on modern techniques to study the determinants of TMC. Noorbakhsh et al. studied the security of female cyclists using tree-based ML algorithms. They mostly considered the built environment features, individuals, and social aspects from the collected data and concluded using the RF algorithm by considering the feature importance that population and social aspects are the most influential factors [27]. Besides, Liu et al. studied the development of new rail transit to achieve a sustainable and efficient transport system to study individual multimodal travel behaviors using the XGBoost ML method. Moreover, they investigate the interrelation between the socio-demographic attributes, built environment, and trip stage characteristics. They concluded that separate stage trips show a stronger impact than the general stage trip, whereas changing a trip's characteristics has a strong impact on individual TMC [28].

Based on the above recent and past studies in the field of TMC, built environment, determinants of TMC, and SWB using conventional and modern techniques, the current papers aim to study (1) socio-demographic and economic variables, (2) time-use and activity travel participation, (3) TMC used for a daily set of activities, and (4) its influence on SWB. Previous studies used travel diary surveys; however, the current study uses a time-use and activity diary, which offers richer information for individual travel behavior and considers multi-dimensional IH and OH activities.

3. DATASET

The survey was intended to collect multi-dimensional data related to TMC and health-related quality of life indicators. The survey was gathered through a face-to-face questionnaire survey using random sampling techniques. By considering special events, local and national holidays, and weather conditions (the same weather as the fluctuation of weather has a great impact on TMC and daily activity), the survey was implemented in September 2013. However, the recruitment of the respondents was conducted in August 2013. As the aim was to gather the data for 21 consecutive days, an agreement was signed between the respondents and surveyors that during the survey period, the respondents would not withdraw from the survey. The survey was performed in the local language, for instance, Bahasa, due to the poor educational background of the respondents. For detailed information about the questionnaire survey and data collection, please refer to [29].

For 21 days in total, the complete dataset included 732 people and 191 families, which corresponds to 0.029% of the population of the Bandung Metropolitan Area (BMA) inner area in 2013. This research comprises 508 participants, or 0.020% of the population of the inner region, after accounting for mislaid data and reliance on children (under seven years old). Table 1 depicts the explanation of individuals.

Table 1

Explanation of the respondents (N = 508)

Variables	Percentage or mean
Socio-demographic characteristics	
Man	52.60%
Woman	48.40%
Worker	39.0%
Non-worker	25.55%
Student	33.45%
Dependent Children (< 15 years)	14.54%
Age 15–22	22.46%
Age 23–44	43.60%
Age 45–55	10.60%
Age over 55 years	9.50%
Medium household income (3–6 IDR)	92.05%
High household income (> 6 million)	7.95%
Trip involvement and travel time consume on weekdays (weekends)	
Daily trips	2.64 (2.30)
Trip chains	1.08 (1.10)
Travel time by a motorized mode (%)	46.60%
Travel time by active mode (%)	28.30%
Travel time by PT (%)	25.10%
Total travel time (minutes)	98.29
Perceived accessibility variables (Travel Time) – minutes	
PT lanes transient through individual location (number)	2.470
Time to CBD	28.70
Time to a government office	16.88
Time to shopping malls	14.55
Time to grocery stores	9.45
Time to recreational area	18.92
Time to PT stop	13.14

The part on household data included information on household composition, people's perceptions of how close or far their places of residence were to the city center, public transit options, and built environment characteristics. As discussed earlier, the activities were categorized as leisure, mandatory, and maintenance activities and then further categorized into IH and OH activities. Each motion diary recorded 23 different forms of activity involvement, which were divided into IH and OH pursuits, as predicted in Table 2. IH mandatory activities included sleeping, drinking, eating, and personal care at home, while OH mandatory activities included attending meetings, working, picking up and dropping off kids, and outdoor dining. Moreover, IH and OH leisure and maintenance activities are categorized based on their nature. Babysitting and household activities are IH maintenance activities, while sports, social events, and volunteering are OH leisure activities, as shown in Table 2.

Table 2

Activity categorization based on IH and OH leisure, maintenance, and mandatory activities

	Mandatory		Maintenance		Leisure	
	IH	OH	IH	OH	IH	OH
Activity Criteria	Sleeping Personal care Eating and drinking at home	Indoor working activities Outdoor working activities Indoor school activities Eating and drinking Dropping/picking up children or others OH sleeping	Household activities Babysitting activities	Sales activities Shopping activities OH maintenance Waiting for PT	Relaxing activities Social and family activities	OH social Outdoor school Organization/volunteer/political activities Sports activities Holiday Other OH

The socio-demographic characteristics is categorized based on gender and travel mode, as shown in Fig. 2 and 3. Males always outnumber females despite the non-workers and divorced rate. As discussed earlier, the transport modes are classified as motorized, non-motorized, and PT. Males use several transport modes due to their involvement in OH mandatory activities. Those from low-income states frequently use all three modes of transport for their daily mandatory, leisure, and maintenance activities. Regarding occupation, workers used the highest number of all three transport modes compared to non-workers and students. In addition, those who are married and who have a senior high school level of education used the highest transport modes compared to the rest of the martial status and education level.

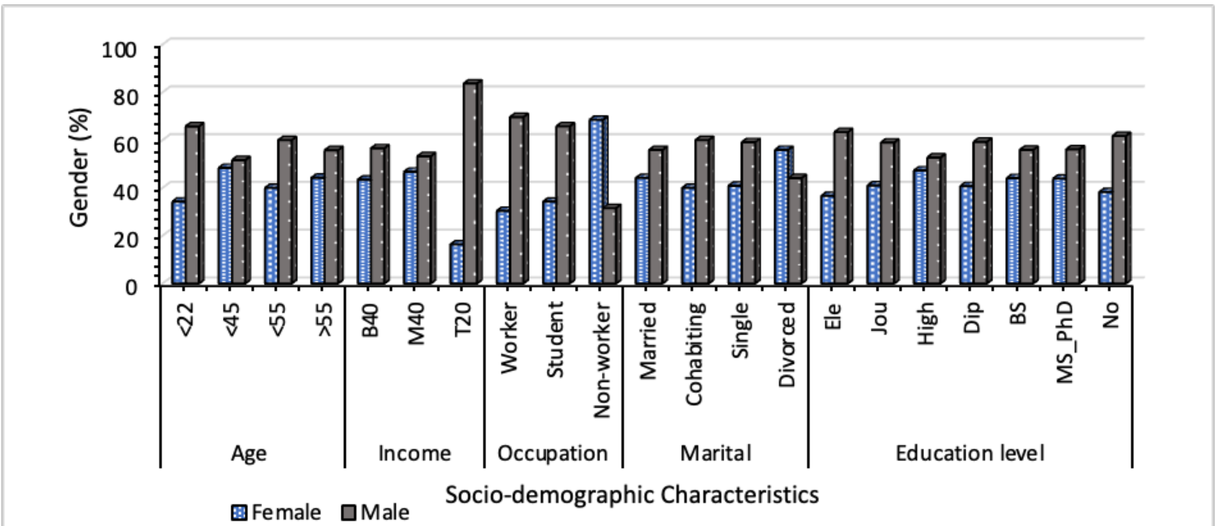

Fig. 2. Socio-demographic classification based on gender

4. TRAVEL MODE CHOICE FOR SEVERAL DAILY ACTIVITIES

Fig. 4 depicts the time-use and activity participation (TU-ATP) for different sets of daily OH and IH leisure, maintenance, and mandatory activities in a week. Fig. 5 illustrates the percentage of transport modes used for several sets of daily activities in a week. Out-of-home mandatory (OHM) activities on weekends decline while IH mandatory, leisure, and maintenance activities rise, indicating that most people work and study on weekdays. Besides, there is a minor rise in in-home maintenance (IHM) and out-of-home leisure (OHL) activities, which shows that individuals perform some leisure activities outside the home on weekends, such as going to the park for recreational activities, participating in sports activities, and shopping.

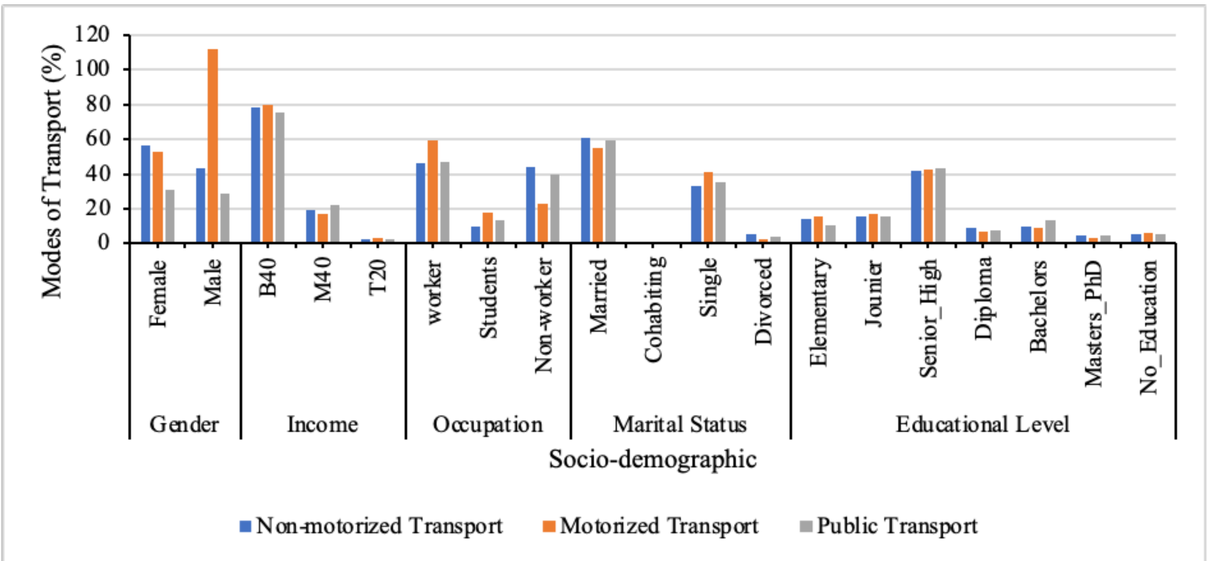

Fig. 3. Socio-demographic classification based on mode of transport

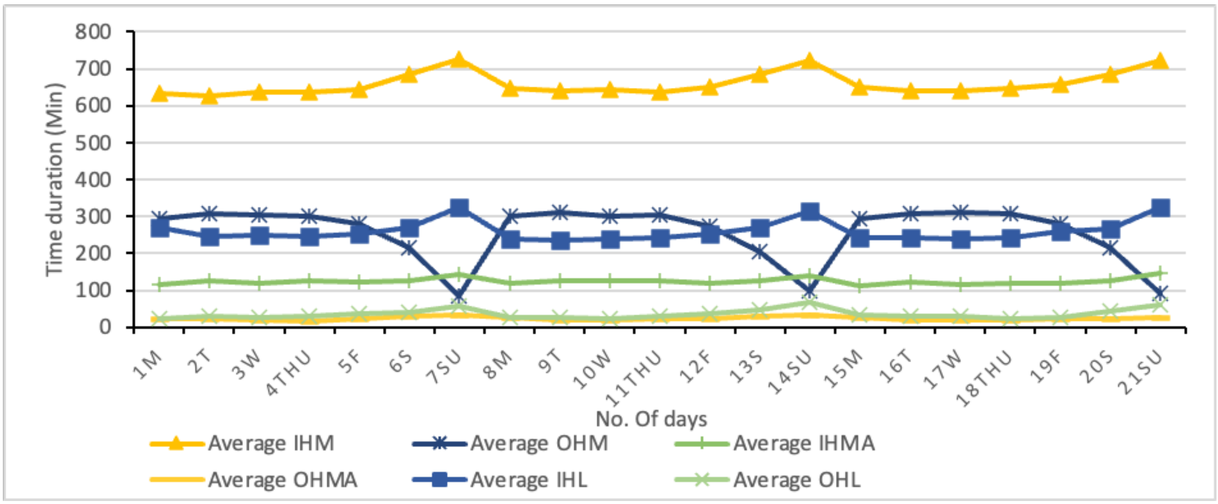

Fig. 4. Time used for diverse activities on a specified day in a week
Notes: IHM = in-home mandatory, OHM = out-of-home mandatory, IHMA = in-home maintenance, OHMA = out-of-home maintenance, IHL = in-home leisure, OHL = out-of-home leisure

Individuals used several transport modes while engaging in several activities on weekends and weekdays. Their main transport mode for daily IH and OH, maintenance leisure, and mandatory activities is motorized transport. There is a slight decrease in motorized transport mode on weekends, which shows that mostly the motorized transport mode is used for traveling to the office, picking up and dropping off kids at school, and other mandatory activities. Besides, there is a gradual increase in non-motorized transport modes and a gradual decrease in PT modes on weekends, showing that most individuals walk and cycle on weekends for OH leisure and maintenance activities. Among all three transport modes, PT was the lowest, which shows that BMA does not have a proper PT system, limited transport line, and minimal access to PT. Moreover, the percentage of non-motorized transport modes exceeded 20% on weekends, whereas PT decreased to 5%. On the other hand, the use of motorized transport reached 70%, which increased the average travel time to 95%, as shown in Fig. 5.

5. MODEL ESTIMATION RESULTS

The statistical analysis is conducted on the basis of the research hypotheses and objectives. Fig. 6 depicts the proposed theoretical mode to see the causal relationship between socio-demographic and economic variables, built environment, TU-ATP, trip parameters, day-to-day travel parameters, and its effect on SWB. Table 3 shows the model estimation results with significant values of the p-value of less than 0.05 due to the CI level of 95%.

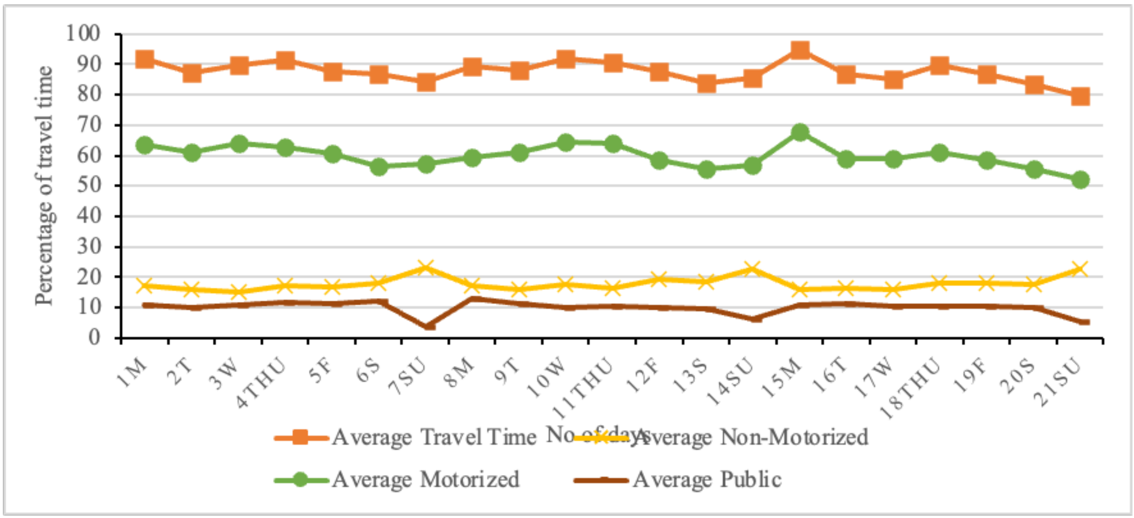

Fig. 5. Time use on diverse transport modes on a specified day in a week

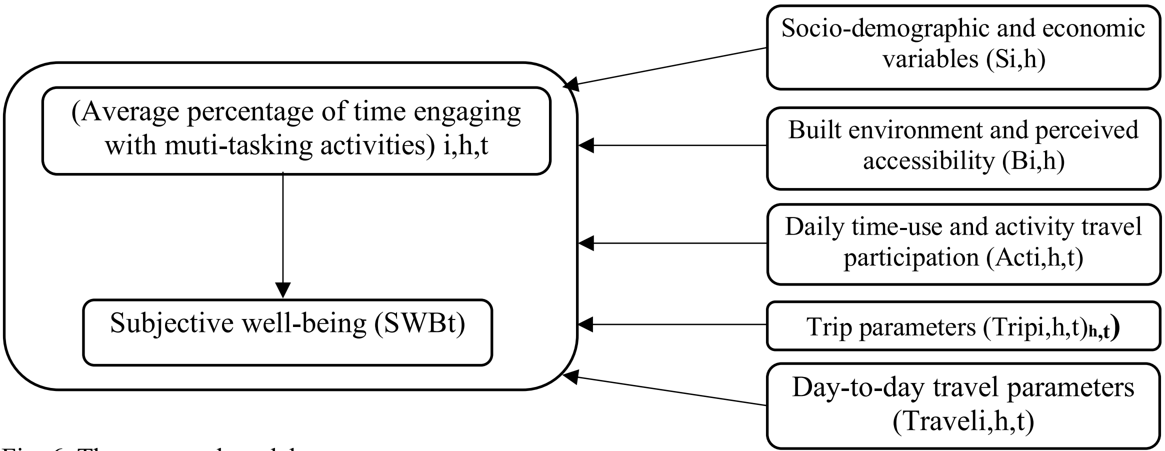

Fig. 6. The proposed model

All the variables on the left side of the model, such as socio-demographic and economic, built environment, daily TU-ATP, trip parameters, and day-to-day travel parameters, are independent variables, whereas the percentages of time engagement with mandatory, leisure, and maintenance activities are used as endogenous variables in the first mode and used as a mediation variable in the second model for the dependent variable of subjective well-being. Mathematical equations are developed based on the exogenous and endogenous variables and multilevel linear regression analysis using SPSS, as shown in equations 1 and 2. Moreover, the unstandardized coefficient B value and t-stat values are used for the causal relationship between the independent and endogenous variables.

Table 4 illustrates a summary of the theoretical model containing the R^2 and adjusted R^2 for both models. Besides, the significance of the model was assessed using the sig value of 0.001, and the influence of exogenous variables on the endogenous variables was assessed using the R^2. For the quantitative research, the R^2 of 0.01 (10%) is satisfactory; however, in the case of the current study, the R^2 was 0.141 (14.1%) and 0.079 for the first model and approximately 8% for the second model. The ANOVA of the model estimation results is shown in Table 5.

$$(Activities)_{i,h,t} = (\alpha_{i,h} + u_i + u_h) + \beta_1 S_{i,h} + \beta_2 B_{i,h} + \beta_3 Act_{i,h,t} + \beta_4 Trip_{i,h,t} + \beta_5 Travel_{i,h,t} + \varepsilon_{i,h,t}\ , \quad (1)$$

$$(SWB)_{i,h,t} = (\alpha_{i,h} + u_i + u_h) + \beta_6 S_{i,h} + \beta_7 B_{i,h} + \beta_8 Act_{i,h,t} + \beta_9 Trip_{i,h,t} + \beta_{10} Travel_{i,h,t} + \beta_{12} (Activities)_{i,h,t} + \varepsilon_{i,h,t}\ . \quad (2)$$

Table 3

Model estimation results (only significant values with a p-value of less than 0.05 are shown)

Variables	Mandatory activities		Subjective well-being	
	Coeff	T-statt	Coeff	T-statt
Constant	-1.490	-13.76	0.748	5.714
Female	Ref	Ref	Ref	Ref
Male	-0.035	-3.992	0.050	4.709
Worker	Ref	Ref	Ref	Ref
Non-worker	-	-	0.129	8.342
Student	-.092	-5.970	0.278	4.720
Dependent Children (< 15 years)	-0.12	-4.134	-0.10	-2.66
Age 15-22	-	-	0.332	7.093
Age 23-44	-	-	0.338	7.581
Age 45-55	-	-	0.303	7.130
Older than 55 years	Ref	Ref	Ref	Ref
Medium household income (3-6 IDR)	0.022	2.205	-0.047	-3.867
Low household income (< 3 IDR)	Ref	Ref	Ref	Ref
High household income (> 6 million)	-0.077	-3.224	-0.197	-6.779
Number of household members	0.011	3.883	-0.03	-10.80
Number of trips	-	-	-0.013	-1.941
Number of trip chains	0.142	11.913	0.036	2.502
Number of PT lines	0.014	3.852	-0.024	-5.492
MT	0.138	8.322	-0.124	-3.522
AT	0.102	2.231	0.221	4.543
PT	0.091	2.098	0.187	5.220
IHM	0.001	16.89	-	-
IHMA	0.001	16.94	-0.001	-2.051
IHL	0.001	16.982	0.012	2.140
OHM	0.001	13.532	0.018	2.144
OHMA	0.002	18.106	-0.001	-6.681
OHL	0.001	17.208	-0.001	-5.097
Endogenous of MTA	-	-	0.56	4.705
Error term	0.391		0.477	
F	59.998		30.775	
R^2	0.141		0.077	
SD	29		30	

Males have a negative correlation with MTA, as they are more engaged in OHM activities and motorized transport modes. Therefore, they have limited access to participate in MTA, which negatively influences them. However, it is positively associated with subjective well-being. A unit increase will cause a 5% increase in daily subjective well-being. Regarding occupations, both the non-workers and students have positive well-being, whereas those who have dependent children in their household are negatively associated with subjective well-being due to tighter time-space constraints and limited time to participate in MTA.

Age group has an insignificant correlation with MTA, whereas it has a positive correlation with daily subjective well-being, which means that if they tend to participate in MTA on a daily basis, it will improve their daily subjective well-being. Moreover, those who are from medium-income households are participating in more MTA, which shows a positive correlation; however, it is opposite with the daily subjective well-being. On the other hand, living in a high-income household has a negative impact on MTA and daily SWB due to the use of motorized transport mode for daily participation in OHM activities, which causes restrictions from participating in MTA, as well as a negative effect on their daily SWB.

Table 4

Model estimation summary

Summary of Model				
Number	R	R^2	Adjusted R^2	Std. Error od Estimate
1 [a]	0.375	0.141	0.138	0.391
2 [b]	0.278	0.079	0.077	0.477

a - activity type dependent variable, b - subjective well-being dependent variable

Table 5

ANOVA of the model

ANOVA					
Model 1	Sum of Square	df	Mean Square	F	Sig
Regression	265.548	29	9.157	59.998	.000 [a]
Residual	1623.411	10637	.153		
Total	1888.960	10666			
Model 2					
Regression	203.300	30	6.944	30.546	.000 [b]
Residual	2423.046	10636	.227		
Total	2626.345739	10666			

a - activity type dependent variable, b - subjective well-being dependent variable

Regarding the trip chains and number of trips, those who have a high number of trips have negative daily subjective well-being, while those having trip chains (from place to place to complete a circle, as shown in Fig. 1) have positive daily SWB. This is due to the involvement of MTA in a trip chain and participating in several sets of OH activities at different locations. The number of PT lines has a positive correlation with MTA, which shows that PT provides more opportunities to participate in more MTA while traveling. A unit increase in PT lines can provide a 1.4% opportunity to participate in more MTA while traveling.

Regarding OH and IH daily leisure, maintenance, and mandatory activities, those participating in all activities are positively associated with MTA, whereas there are some variations in the SWB and daily OH and IH leisure, maintenance, and mandatory activities. Those who are participating in IHL and OHM activities while doing MTA have a positive correlation with daily SWB, whereas others are the opposite. The current study shows that MTA can be used as an intermediate variable between the socio-demographic, built environment, travel and trip parameters variables, and daily subjective well-being, which supports previous research [6].

The conceptual model was developed and analyzed based on the suggested hypotheses. From the statistical analysis, it was absorbed that all three hypotheses were rejected. The socio-demographic and economic variables are positively associated with SWB, whereas travel mode choice and type of activity enhance SWB. Both the models have a significant correlation, $p < 0.005$ (CI 95%), $R^2 = 0.141$.

6. CONCLUSIONS

The current study aimed to study and statistically evaluate different transport modes used for daily activities and their influence on daily SWB. This study examined the association between spatiotemporal variables on the percentage of time spent on travel mode choice and how it interacts with individual regular SWB. It used hierarchical linear regression and a multi-dimensional 21-day household TU-ATP. Based on the model estimation findings, it is possible to draw the following conclusions.

In contrast to the outcomes of the descriptive study, the results of the hierarchical linear regression demonstrate that socio-demographic and economic variables are positively correlated with different transport modes. Those who are from low-middle class income are more engaged in several sets of daily activities. Besides, those who are exposed to PT and tend to use non-motorized transport modes for daily activities have more opportunities to partake in more physical activities, which is positively related to daily SWB than those who use a private vehicle such as high-income household members, which has a negative impact on SWB. As individuals live further from some of their fundamental facilities, for instance, the CBD, government buildings, and shopping malls, they tend to use different transport options. A unit increase in private vehicles has a 13.8% positive association with daily activities but a 12.4% negative association with SWB. Contrarily, a unit increase in active and PT results in a 10.2% and 9.1% positive association with daily activities and a 22.1% and 18.7% positive association with daily SWB.

Any commitment to engage in outside-the-home discretionary activities, however, seems to enhance everyday well-being. Besides, the current study confirms that those who perform more IHL and OHM activities have relatively high SWB. A unit increase in IHL activities is 1.2% positively correlated with SWB, whereas a unit rise in OHM activities is 1.8% positively associated with SWB. Therefore, the existing research will support the policymakers to adopt their policy based on model estimation results and will allow individuals to perform more activity using active and PT, which can enhance their health parameters and daily SWB.

Moreover, the R^2 for the socio-demographic and economic variables; travel mode choice; IH and OH leisure, mandatory, and maintenance activities; and SWB were 0.141, which is higher than 10%. The R^2 of 0.1 (10%) can be deemed satisfactory for endogenous variables in psychology studies, travel behavior studies, and health research, whereas 0.15 (15%) is considered high. The R^2 values for the current study model were almost 15%, which is considered high and shows strong correlations among independent and dependent variables.

Future scholars may want to solve several problems with the present research despite its substantial theoretical contributions. The current research studied the association between travel mode choice and SWB. Future researchers can extend the study using the onboard MTA as a mediation variable regarding transport mode choice to study SWB, as it is widely believed that performing onboard MTA during travel enhances SWB.

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