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Travel Mode Choice Prediction to Pursue Sustainable Transportation and Enhance Health Parameters Using R

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Abstract: Travel mode choice (TMC) prediction, improving health parameters, and promoting sustainable transportation systems are crucial for urban planners and policymakers. Past studies show the influence of health on activities, while several studies use multitasking activities and physical activity intensity to study the association between time use and activity travel participation (TU and ATP) and health outcomes. Limited studies have been conducted on the use of transport modes as intermediate variables to study the influence of TU and ATP on health parameters. Therefore, the current study aims to evaluate urban dependency on different transport modes used for daily activities and its influence on health parameters to promote a greener and healthier society and a sustainable transportation system. Pearson's Chi-squared test was used for transport mode classification, and multinominal logit models were used for regression using R programming. A total of five models were developed for motorized, non-motorized, public transport, physical, and social health to study the correlation between transport modes and health parameters. The statistical analysis results show that socio-demographic and economic variables have a strong association with TMC in which younger, male, workers and high-income households are more dependent on motorized transport. It was found that a unit rise in high-income causes a 4.5% positive increase in motorized transport, whereas it negatively influences non-motorized and public transport by 4.2% and 2.2%, respectively. These insights might be useful for formulating realistic plans to encourage individuals to use active transport that will promote sustainable transportation systems and a healthier society.

Keywords: urban mobility; transport modes; sustainable transportation; health parameters; activity travel participation

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1. Introduction

To understand individual travel behaviors, activity travel participation must be studied, such as when, where, why, and how the people travel. Past studies used several advanced methods for the estimation of mobility demands, such as trip-based models, activity-based models, and tour-based models. Trip-based travel behavior modeling focuses on analyzing individual trips as the basic unit of analysis. However, the activity-based approach overcomes the limitations of the trip-based approach and provides a more comprehensive understanding of travel behavior by considering the interdependencies between activities and travel. Axhausen et al. used a six-week travel diary survey approach to observe the rhythm of daily life [1], whereas Bifulco, Cartenì, and Papola studied an activity-based approach for complex travel behavior modeling by explicitly addressing activity participation and activity planning [2]. An alternative tour-based mode choice model was offered by Miller, Roorda, and Carrasco. The same anchor points are used at the start and finish of both home-based and non-home-based tours and excursions [3]. In addition, Nurul Habib designed a model to capture correlations among random components influencing commuters' mode choice, work start time, and work duration decisions.

The model's primary objective is to forecast employees' work schedules based on mode selection [4]. In addition, Ho and Mulley developed two models for weekdays and weekends to study joint household travel arrangements and mode choices [5]. The current study uses activity-based approaches to gather time-use and activity travel participation data at individual and household levels for 21 consecutive days, which highlight both weekdays and weekends.

Furthermore, rather than a pleasant, inexpensive, and faster means of transportation, the individual should pick healthier and more ecologically sustainable commuting routes and travel mode choices (TMCs). The prediction of TMCs is crucial for urban planners and policymakers to provide a safer, sustainable, congestion-free, and environmentally friendly transportation system and network [6]. However, past studies claimed that several determinants influence an individual's TMC for daily activities [7,8]. For instance, most individuals prefer to use private vehicles over public ones due to the total travel time and travel distance [9,10], whereas Termida et al. concluded that weather conditions significantly affect activity-travel patterns and TMCs [11]. R. Buehler claimed that Americans may reduce their car use by increasing fuel prices, while Germans prudently use cars due to the high cost of car travel [12]. Therefore, it is vital to understand and predict the determinants of TMCs and their implications on health parameters to promote a sustainable transport system and a healthier society.

Transport, health, the built environment, and climate are interwoven with each other, where transport influences health parameters and health influences transport options, as depicted in Figure 1. Active transport promotes physical activity, enhances health parameters, and reduces air and noise pollution, but it also exposes individuals to the risk of traffic injuries and air pollutants [13]. However, the health condition influences individual activity and travel parameters [14,15]. For instance, a person with disabilities will be unable to travel via active transport, whereas having social and mental health issues, such as stress and depression, influence public transport (PT) options. However, PT provides an opportunity to engage in more multitasking activities that enhance subjective well-being [16–18]. In addition, the lack of availability of infrastructure and accessibility influences transport options. Therefore, providing all the basic amenities at a walkable distance encourages the individual to use non-motorized transport (NMT) [19], whereas providing infrastructure and accessibility of PT to all basic amenities encourages the individual to use PT [20]. Aghaabbasi et al. concluded that sidewalk availability, transit station conditions, and bike paths were the most influential factors in choosing active transport [21]. The red circles in Figure 1 show the mediation variables whereas the red arrow shows the direct effect of health on travel behaviors.

Promoting sustainable transportation systems, improving health parameters, and the reduction of greenhouse emissions (GHGs) are crucial for urban planners and policymakers. Among many significant contributing factors to GHG, global road transportation shares around 14% of GHGs to the globe, 29% of all GHG emissions, as depicted in Figure 2 [22,23]. The European Union and the US aim to neutralize CO_2 emissions from the transportation sector by 2050. Therefore, Zhang et al. concluded that active and public transport are encouraged in urban areas to reduce GHG emission [24], whereas Xu et al. claimed that electric vehicles (EVs) in Europe significantly reduce GHG emissions [25].

Sufficient studies have been conducted that show the influence of health parameters on activities, while limited research has been conducted on the influence of transport modes on health outcomes. Past studies used different intermediate variables, such as multitasking activities and physical activity intensity, to enhance health parameters; however, according to the author's view and the latest studies, there are limited studies that utilized transport modes as intermediate variables to study the correlation between ATP and health parameters. Therefore, the current study aims to use transport modes as an intermediate variable to study the correlation between transport-related daily activities and health outcomes to pursue sustainable transportation growth and a healthier society. The current study added new insights to the existing literature (1) about the determinants of TMCs, especially through sociodemographic and economic perspectives; (2) urban dependency on TMCs; (3) shifting the urban dependency from private vehicles towards green travel modes and public transport to promote sustainable transportation systems; (4) enhancing health outcomes; and (5) providing a green and sustainable society. The outcomes have the potential to promote active transport and PT, formulate realistic planning plans, and help policymakers develop their policies based on travel demands to meet individual needs.

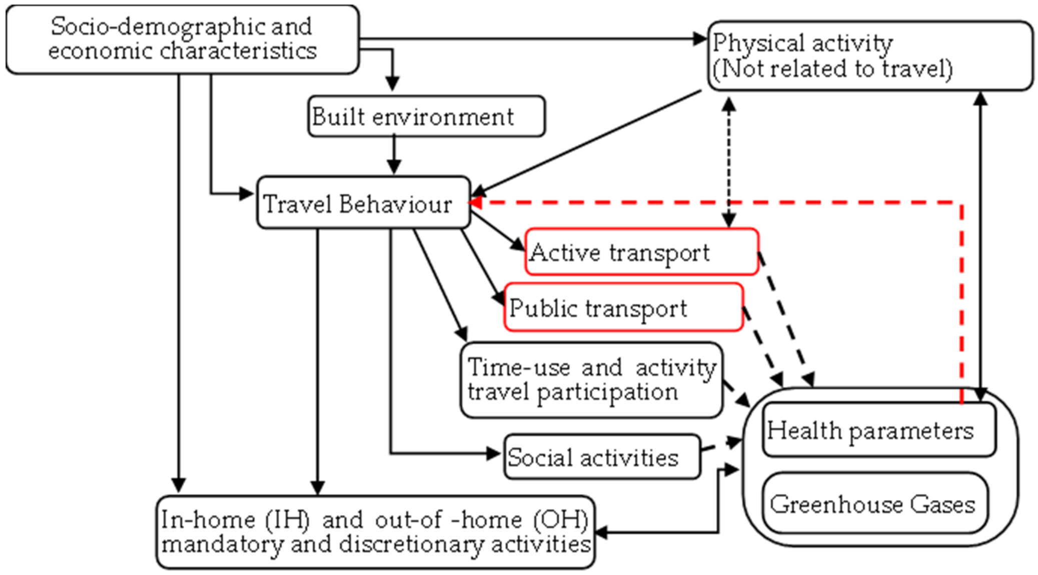

Figure 1. Conceptual model for association among travel behaviors, the built environment, type of activity, TMC, health outcomes, and GHG emissions.

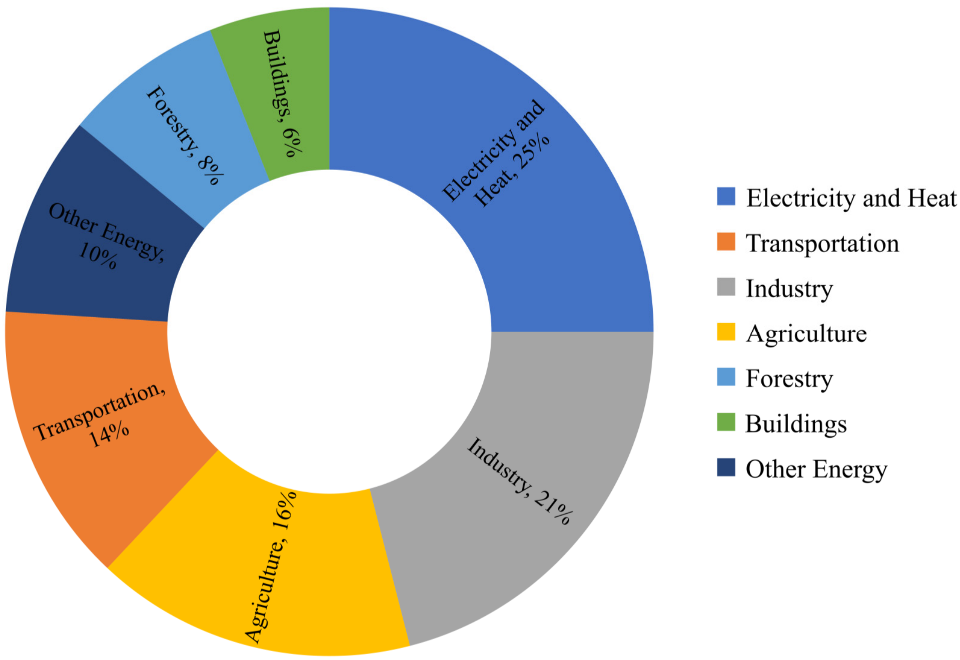

Figure 2. Global GHG emissions by economic sectors [26].

The current study will help the Bandung Metropolitan Area (BMA), Indonesia, in its efforts to use NMT modes to improve citizen health. The goal of the current research is to provide practical planning strategies that will motivate, nudge, inform, and empower people to use active transportation to improve their health and advance a more environmentally friendly and health-conscious society.

Research Questions

Based on the above discussion, the current research will be able to answer the following research questions.

1. Are the individuals willing to shift their short car trips to active transport?
2. Do activity travel participation and different transport modes used for daily activities positively influence health parameters?
3. Can the transport mode mediate the correlation between daily activities and health and significantly enhance health parameters?

The rest of the paper proceeds as follows. Section 2 discusses some of the pertinent studies. Section 3 describes the materials and methods employed in this research study. Results and discussions are presented in Section 4. Finally, Section 5 concludes the research study and provides some insights and recommendations.

2. Literature Review

The selection of a specific mode choice for a journey in an urban area is influenced by contextual, objective, and subjective factors. Ababio-Donkor et al. studied subjective factors, such as the role of personal norms, while choosing a specific transport mode for commuting and concluded that personal norms have a significant positive impact on individual travel behaviors, whereas pro-environmental attitudes make individuals likely to use sustainable transport modes [27]. A. Abulibdeh used Shapley's Additive explanation (SHAP) to investigate the rank of each input variable of the new Doha Metro on TMCs. He concluded that travel time, number of travelers and bags, and reimbursement of parking fees are the most significant factors in choosing the Metro [8]. In addition, Soomro et al. studied the factors that influence the willingness of travelers to choose the BRT green line using a contingency table approach in conjunction with a Chi-square test and binary logistic regression in Karachi, Pakistan. They concluded that the imposition of parking fees at workplaces deters individuals from parking at the workplace, which encourages them to choose the BRT green line over private vehicles [28]. Mehmood et al. studied the impact of proposed bus rapid transit (BRT) on a modal share of private vehicles using a binary logit model in Peshawar, Pakistan. They concluded that the vehicle operating cost was the most influential factor that affected the car users to shift to BRT in urban areas [29].

Due to technological development, recent studies utilize both traditional and modern techniques for the determinants of TMCs. For instance, N. F. M. Ali et al. predict the TMC using the Discrete Choice Model (DCM) and Machine Learning (ML) algorithms. They concluded that the Neural Network outperforms Binary Logistic Regression, whereas based on feature importance, they asserted that the waiting time, total travel time, and distance between the last stop and destination are the most significant features influencing individual TMCs [30]. Cheng et al. applied several ML and conventional techniques to study the TMC and concluded that ML algorithms outperformed conventional techniques. They concluded that the most crucial factor that influences TMC prediction is the total travel time [31]. Chang et al. proposed a hybrid model of the unsupervised Denoising Autoencoder (DAE) combined with the supervised Random Forest (RF) for the prediction of TMCs [32], whereas Qian et al. classify the imbalance of TMC to work data using an adjustable support vector machine (SVM) due to the assumption and limitation of typical the SVM for handling the imbalanced data. They concluded that the hyperparameter optimization of the adjustable kernel SVM outperforms the typical SVM, where the number of drivers, reason for not walking, and number of adults over 18 years are the most significant features for TMCs to work [33].

Health and transport are related in both direct and indirect ways, with health directly influencing transport alternatives and transportation indirectly influencing health indicators [34–36]. Hägerstrand's temporal geography theory, which was first presented in the 1970s, holds that an individual's health might be a capability restriction that prevents them from traveling or engaging in certain activities [37,38]. However, transport-related

PA enhances health outcomes. Dharmowijoyo et al. studied the effect of the built environment and health on multitasking activities (MTAs) and concluded that health parameters (especially social health) influence MT, which means that health is a part of capability constraints [39], whereas Ali et al. studied the effect of MTA on subjective well-being and concluded that PT offers more opportunities to engage in MTA, which enhances subjective well-being [16,40]. Moreover, Hamadneh and Esztergár-Kiss studied the effect of MTA and tools carried on the perceived travel time and concluded that MTA has a positive correlation and enhances the trip time where women are engaged more than men [17].

In recent years, the association between transport and health gained significant attention. Numerous investigations have been carried out to examine the impact of daily physical activity, both associated and unassociated with transportation, on overall [41,42] and physical health [43,44]. Active transport is extensively studied for its positive influence on health. For instance, a systematic review by Yang et al. found consistent evidence of the protective effect of active transportation on overall mortality and cardiovascular disease [45]. In addition, active commuting to work or school lowers stress, anxiety, and depression. Richardson et al. concluded that active commuting has a positive impact on mental well-being [46]. On the other hand, intense traffic and hazardous road conditions cause more collisions that result in fatalities or serious injuries. Participating in leisure time PA has a positive association with physical and social health [47], whereas work-related multitasking activities have a negative impact on mental health [48]. According to a 2023 survey, 73% of American respondents chose the private mode, underscoring the car's crucial importance in daily life in the country [49]. Ding et al. studied sedentary transport and posed health risks and found a positive correlation between sedentary travel and adverse health outcomes [50].

As evident from the literature above, various methods have been proposed by different researchers to move towards sustainable transport modes. However, the quantitative findings specifically focusing on how these mode choices impact health parameters remain largely unexplored. Addressing the research gap and answering the research questions were the main motivations behind this study. In addition, past studies have used physical activity intensity, multitasking activities, lifestyle habits, personal preferences, attitudes, and the living environment as intermediate variables to study the effect of daily activities and transport mode options on health parameters. However, according to the author's view and recent studies, there is a lack of studies on using transport modes as intermediate variables to study health outcomes. To fill the research gap, the current study aims to use motorized transport, public transport, and active transport as intermediate variables to investigate health outcomes. Moreover, the prediction of the TMC, enhancement of health parameters, and promotion of sustainable transportation are crucial for urban planners and policymakers. Therefore, the current study aims to study the TMC used for daily activities and its implications on health parameters to promote a greener and healthier society and a sustainable transportation system.

3. Materials and Methods

3.1. Study Site Background

Over the last few decades, Indonesia has witnessed significant economic expansion and development. The provincial capital of West Java, Bandung, is one of Indonesia's most significant urban areas and a key hub because of its strategic location, economic potential, and status as a hub for education and tourism. Bandung has a population of around 2.5 million, but when the neighboring towns and districts are taken into account, the population rises to nearly 8 million. With major arterial roads and highways linking it to Jakarta and other regions of Java, Bandung offers an immense road network. Like its road system, Bandung offers a strong railway network that is essential to the city's passenger and freight transportation. The city has several public transportation choices, including taxis, buses, angkot (minivans), and the Trans Metro Bandung bus system, which is a more contemporary form of transit. Angkot, which travels around the city routes, is a common and inexpensive means of transportation for the inhabitants of Bandung. Most individuals use private vehicles for daily commuting, whereas car rentals help tourists travel around the city. The city is working to enhance its transportation infrastructure to lessen traffic jams and encourage greener modes of transportation. By considering all these aspects, the current study chooses the Bandung Metropolitan Area as a study site.

3.2. The 2013 BMA Data Set

A questionnaire survey was developed to gather face-to-face questionnaire survey data from the respondents. The Bandung Metropolitan Area (BMA) questionnaire survey gathers multidimensional data at individual and household levels, which mainly consists of three main parts. The first part is the household survey that contains six (6) sections, i.e., the household composition, accommodation, household income, travel behavior, subjective neighborhood, and physical disability. The second part of the survey contained the TU and ATP survey, which consists of IH and OH mandatory, maintenance, and leisure activities, daily perception, time spent on an activity, modes of transport used for the activity, the intensity of the activity (frequency and duration), and a discussion with other and within the family followers. Finally, the third part of the survey is health-related quality of life (QoL), which mainly focuses on health parameters, such as the physical and social aspects of individuals. The survey was conducted in Bahasa Indonesia (the local language) due to the low education level and enlistment among the locals. Data were gathered using probability and non-probability sampling techniques with random selection and convenience procedures after a frontal encounter among inspectors and possible responders. The sampling unit was the inhabitants of BMA, and the data were gathered for 21 consecutive days with a total sample size of 732 individuals and 191 households. As the survey was designed for 21 consecutive days, a commitment letter was signed between the respondents and surveyors to not pull back from the survey during August and September 2013.

For cross-sectional and longitudinal studies, it is vital to have a specific timeframe for the data collection. The current study was longitudinal as it collected the data for 21 consecutive days, where August and September were chosen as a timeframe for the current study. In August, the participant recruitment and the introduction of the survey were conducted, while September was chosen for the survey's implementation because there were no noteworthy occasions, public holidays, or other events that would have caused respondents to deviate from their regular routines. Any new legislation that may materially modify the gathered dataset during the time gaps after the survey has been gathered has not been discovered. However, there are some minor changes in the transport mode and infrastructure, which do not deeply affect the current survey. The BMA dataset was thus sufficient for the current investigation.

For a statistical analysis to accurately reflect the complete population and allow for generalization, a sufficient number of data samples must be collected from a specific population. Therefore, several formulas are introduced to calculate the number of respondents from a given population. For instance, in 1967, Yamane [51] and in the 1970s, Daryle W. Morgan and Robert V. Krejcie [52] proposed a formula to collect the required number of respondents as shown in equation 1 [53]. On 21 consecutive days, the complete dataset included 732 people and 191 families, which corresponds to 0.029% of the inhabitants of the BMA's innermost area in 2013. When dependent children (those under seven years old) and missing data are taken into consideration, the research includes 508 respondents, representing 0.020% of the internal region's population in 2013. Table 1 depicts the explanations of the respondents.

$$\mathrm{n} = \frac{N}{1 + Ne^2} \tag{1}$$

where e is the essential degree of accuracy (3%, 5%, or 7%), n is the sample magnitude, and N is the population magnitude.

Table 1. Explanation of the individuals (N = 508).

Input Data	Mean/Percentage
Gender	
Female	43.3%
Male	56.7%
Age	
Below 22 year (adults)	20.7%
Below 45 years (younger adults)	48.4%
Below 55 (older)	20.7%
Above 55 (aged)	10.2%
Income	
T20 (top 20%)	78.7%
M40 (middle 40%)	18.5%
B40 (below 40%)	2.8%
Occupation Status	
Student	14.4%
Worker	53.1%
Non-worker	32.5%
Marital Status	
Married	57.5%
Cohabiting	1%
Single	37.8%
Divorced	3.7%
Education Level	
Elementary	14%
Junior	16.3%
Senior-high	42.5%
Diploma	7.7%
Bachelor	10.1%
Postgraduate	3.7%
No-education	5.7%
Dependent children	30.60%
Modes of Transport	
Active Transport	30.9%
Motorized Transport	50.8%
Public Transport	18.3%

3.3. Household Survey

The survey's data were gathered at the household level and included questions about physical disabilities, dependent children living in the home, type of housing and ownership, neighborhood, household income, and property and internet access. However, for the current study, only the household composition that contains sociodemographic characteristics, household income, dependent children, and travel behavior was considered. The sociodemographic characteristics are composed of gender (male and female), age (above 15 to above 55), occupation (worker, student, and non-worker), marital status (single, married, cohabiting, and divorced), and education level (elementary, junior, high-school, bachelor, master, Ph.D., and no-education). However, the income status contains the top 20% (T20), medium 40% (M40), and below 40% (B40).

3.4. Time-Use and Activity Travel Participation (TU and ATP)

Both the travel-based and activity-based approaches were considered in the past study to study travel behaviors; however, the activity-based approach provides insightful information on daily activity and TM. The current study developed a questionnaire survey for the TU and ATP to gather activity-based data and study travel behavior. The survey contained daily in-home (IH) and out-of-home (OH) mandatory, maintenance, and leisure activities and TM. However, only different transport modes were considered for the present research to achieve the study's aim and goal. The TU and ATP survey was set up at a 15 min interval to make it easier for the surveyor and responders to understand. This results were in 96 sections and 1440 min (24 h) in a day. When addressing people's time allocation to a specific activity utilizing the TU and ATP surveys, less bias is introduced. Possible bias occurs in a dataset when a certain group within a population is underrepresented or overrepresented. In addition, it also occurs when the data-collection method is non-random sampling. The current study used random sampling techniques that were equally accessible and relevant to all demographics and considered a broader and more diverse population group to reduce the bias in the dataset. The respondents were asked to mention the transport mode used for every 15 min interval of activity and classified the different TM for several daily activities.

3.5. Household Physical Activity and Health-Related Quality of Life (QoL)

This part of the survey was divided into four main categories: lifestyle habits, household physical and social activities and their intensities, health-related QoL, and communication with the same and other family members. For the current study, only the health-related QoL variables, such as physical and social health parameters, were used, which are based on SF-36 (short Form-36). The SF-36 questions contained eight subscales that have been adopted by more than eleven countries [54]. The health-related QoL questionnaire contains questions and subscale indicators for all health parameters, such as PH, SH, and MH. However, the current study only focuses on the individual PH and SH. Table 2 depicts the subscales of physical and social health.

Table 2. Health-related QoL (Health Indicators).

Health	Physical Health (PH)	Social Health (SH)
Indicators	Physical functioning (PF) Limitation on role functioning because of PH (RP) General health (GH) Bodily pain (BP)	Limitation on role functioning because of PH (RP) Limitation on role functioning because of emotional problems (RE) Social functioning (SF)

3.6. Statistical Tools

Both SPSS version 26.0.0 and RStudio 4.2.3 were used for the statistical analysis. SPSS was used for descriptive statistics, frequencies, compute variables, factor score analysis, and bivariate analysis. However, R was used for the multivariate analysis and Hierarchal Structural Equation Modeling (SEM) using Non-linear and Linear mixed effects (NLME) models and Multi-Level (ML) regression analysis. Factors score analysis is a statistical method used to reduce a large number of observed variables into a smaller number of latent variables or factors that capture the underlying structure of the data. When one variable is anticipated from multidimensional data, the Varimax and Promax rotations are utilized [55]. The current study used SF-36 health-related QoL, which contained subscales and indicators as shown in Figure 3, and every indicator consists of several questions for the prediction of physical and social health. Therefore, factor score analysis is used with fundamental principal mechanisms and a Promax rotation of Kappa 4 to group the variables in a tiny cluster. The core aim of the factor examination is to recap the data in a way that makes the connection easy to comprehend and analyze. To find the influence of independent variables ($X1$, $X2$, $X3$, ……, Xn) on the dependent variables (Y) with a standard error of estimates (ε), multiple linear regression analysis and SEM were performed using Equation (2).

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

A total of five models were developed in the current study; the TM (NMT, MT, and PT) was used as dependent variables in the first three models, whereas all sociodemographic and economic values were treated as independent values. In addition, TM was used as an intermediate variable in the 4th and 5th models, the PH and SH were the dependent variables, and the socio-demographic and economic variables were the independent variables. The confidence interval (CI) of 95% was used, so the significance of the model with a *p*-value of 0.05 was recorded.

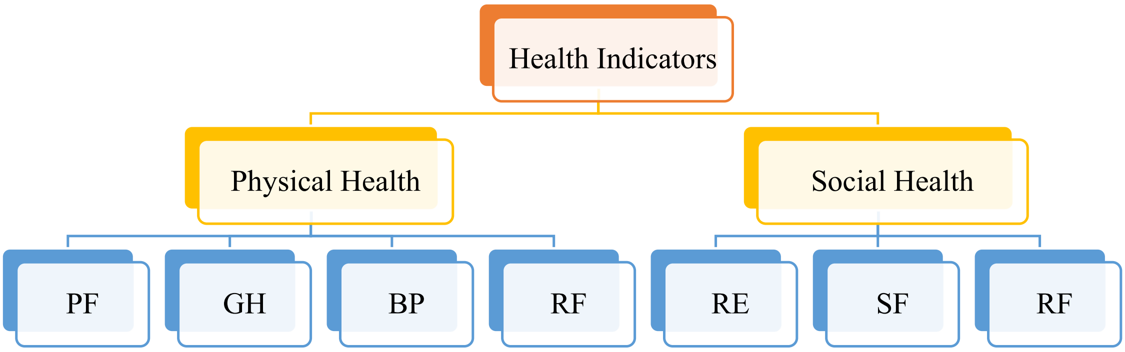

Figure 3. Health-related QoL indicators introduced by Zhang [14].

4. Results and Discussion

4.1. Classification of Gender-Based on Socio-Demographic Characteristics

The first part of the questionnaire survey contained socio-demographic and economic characteristics, which were categorized based on gender to investigate the distribution and responses of the respondents. Most of the inhabitants of BMA belong to low-income or below 40% income (B40) households, which were the highest compared to medium-income (M40) and high-income or top 20% (T20) households, as shown in Figure 4. The percentage of workers and non-workers was higher representing the low education level and low-to-medium income status. Therefore, the questionnaire was prepared, and the data were gathered in the local language (Bahasa Indonesia) due to the poor/low education level, where most of the individuals studied at the high school level, while few people went for postgraduate studies.

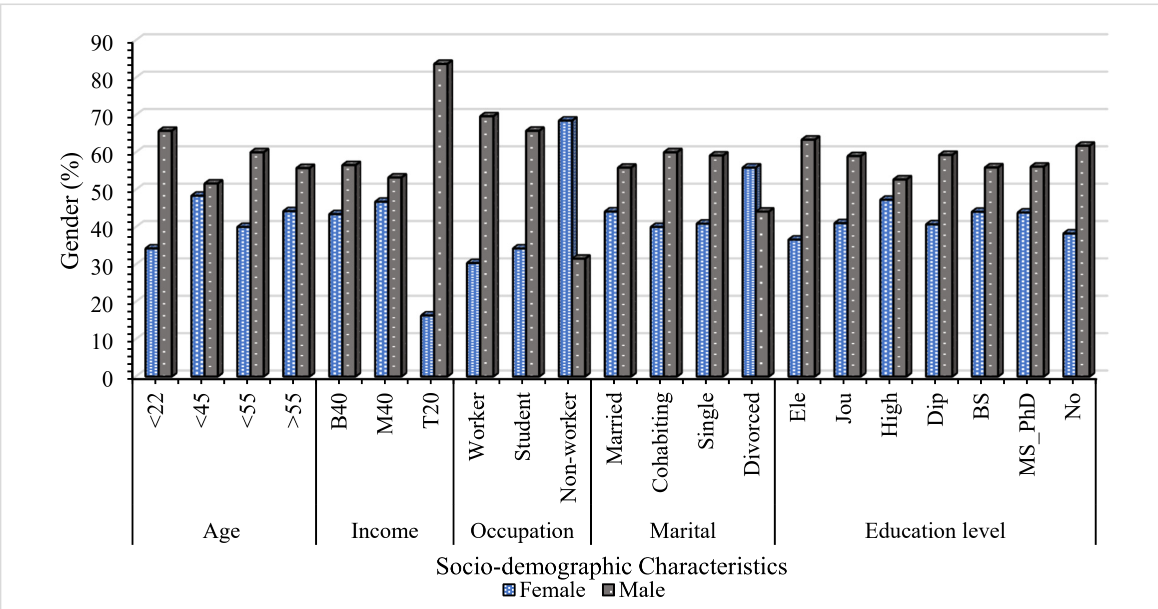

Figure 4. Percentage of socio-demographic classification based on gender.

4.2. Classification of Travel Mode Based on Socio-Demographic Characteristics

The results from the questionnaire included inquiries on daily TM use for various sets of activities on a particular day. For instance, do you have access to a private vehicle? How many private vehicles do you have in your household, how often do you use PT or NMT, do you have access to PT, etc? Table 3 depicts the number or percentage of respondents who used NMT, MT, and PT for 21 consecutive days. For instance, among 508 respondents for 21 consecutive days (10,668), a total of 3485 genders used NMT, of which 1940 females contributed 55.66% and 1545 males contributed 44.33% to NMT use, which shows that most of the females used NMT. For a single day, on average, approximately 92 females (1940/21 = 92.38) and approximately 74 males (1545/21 = 73.57) used NMT. In addition, males are more dependent on MT, which contributed 67.66%, whereas females contributed 32.33%. In terms of PT, 922 females choose PT for 21 consecutive days, whereas 834 males travel using PT, which shows that females use a higher percentage of PT than males. There were similar explanations for the age, household income, occupation, marital status, and education level with different percentages. In terms of occupations, workers and students used high MT compared to PT and NMT, whereas non-workers were the opposite, as shown in Figure 5. Those from low-income (B40) show a high percentage of all three modes of transport. In terms of educational level, those individuals who studied at the high school level use all three TMs to and from school and show the highest TM use compared to the rest of the education level. Overall, males and individuals from 22 to 55 years old are most dependent on MT, while aged and females are using NMT and PT.

Table 3. Classification of travel mode based on socio-demographic characteristics.

Variables	Non-Motorized (%)	Motorized (%)	Public (%)	Total
Gender				
Female	1940 (55.66)	1757 (32.33)	922 (52.53)	
Male	1545 (44.33)	3670 (67.66)	834 (47.48)	10,668
Total	3485	5427	1756	
Age				
Below 22 years (adults)	780 (22.05)	1227 (20.74)	250 (20.64)	
Below 45 years (younger adults)	1686 (47.681)	3280 (55.46)	686 (56.64)	
Below 55 (older)	610 (17.25)	952 (16.09)	156 (12.78)	10,668
Above 55 (aged)	462 (13.00)	457 (7.69)	122 (9.90)	
Total	3538	5916	1214	
Income				
B40 (below 40%)	2588 (78.66)	4329 (79.90)	1476 (75.57)	
M40 (middle 40%)	635 (19.24)	906 (16.72)	435 (22.22)	10,668
T20 (top 20%)	69 (2.097)	185 (3.37)	45 (2.15)	
Total	3292	5420	1956	
Occupation Status				
Worker	1532 (46.57)	3221 (59.45)	910 (46.59)	
Student	323 (9.76)	947 (17.48)	267 (13.57)	10,668
Non-worker	1437 (43.68)	1252 (23.07)	779 (39.84)	
Total	3292	5420	1956	
Marital Status				
Married	1994 (60.61)	2974 (54.89)	1161 (59.45)	
Cohabiting	26 (0.73)	56 (1.03)	26 (1.28)	
Single	1093 (33.22)	2246 (41.45)	691 (35.28)	10,668
Divorced	179 (5.44)	144 (2.62)	78 (3.99)	
Total	3292	5420	1956	

Table 3. *Cont.*

Variables	Non-Motorized (%)	Motorized (%)	Public (%)	Total
Education Level				
Elementary	453 (13.77)	840 (15.50)	198 (10.14)	
Junior	517 (15.71)	922 (17.02)	304 (15.57)	
Senior-high	1388 (42.13)	2293 (42.32)	851 (43.57)	
Diploma	294 (8.94)	374 (6.87)	152 (7.78)	10,668
Bachelor	327 (9.94)	486 (8.97)	258 (13.21)	
Postgraduate	145 (4.41)	164 (3.03)	93 (4.61)	
No-education	168 (5.11)	341 (6.29)	100 (5.12)	
Total	3292	5420	1956	

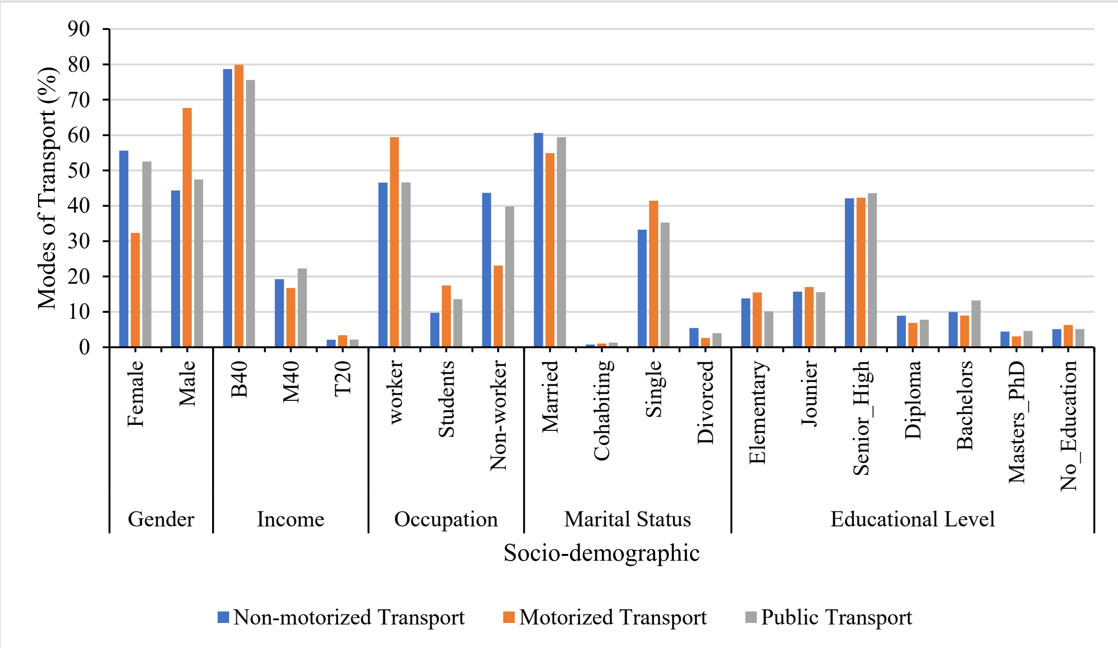

Figure 5. Urban dependency on transport modes.

Figure 6 depicts the correlation of socio-demographic characteristics with physical and social health. Those who are younger are more dependent on NMT and PT, having a positive correlation with PH and SH, while those who are over 45 years old are highly dependent on MT, which negatively influences their PH and SH. In addition, males are found to have a positive correlation with PH and SH due to the high number of participations in out-of-home mandatory and leisure activities daily, whereas females are the opposite. Those who are from high-income households are largely accessible to MT, which negatively influences their PH and SH, whereas low-income households are the opposite. Moreover, workers participating in more out-of-home activities have a positive association with PH and SH, whereas non-workers are the opposite. In addition, students who are more dependent on NMT and PT are positively associated with PH and SH.

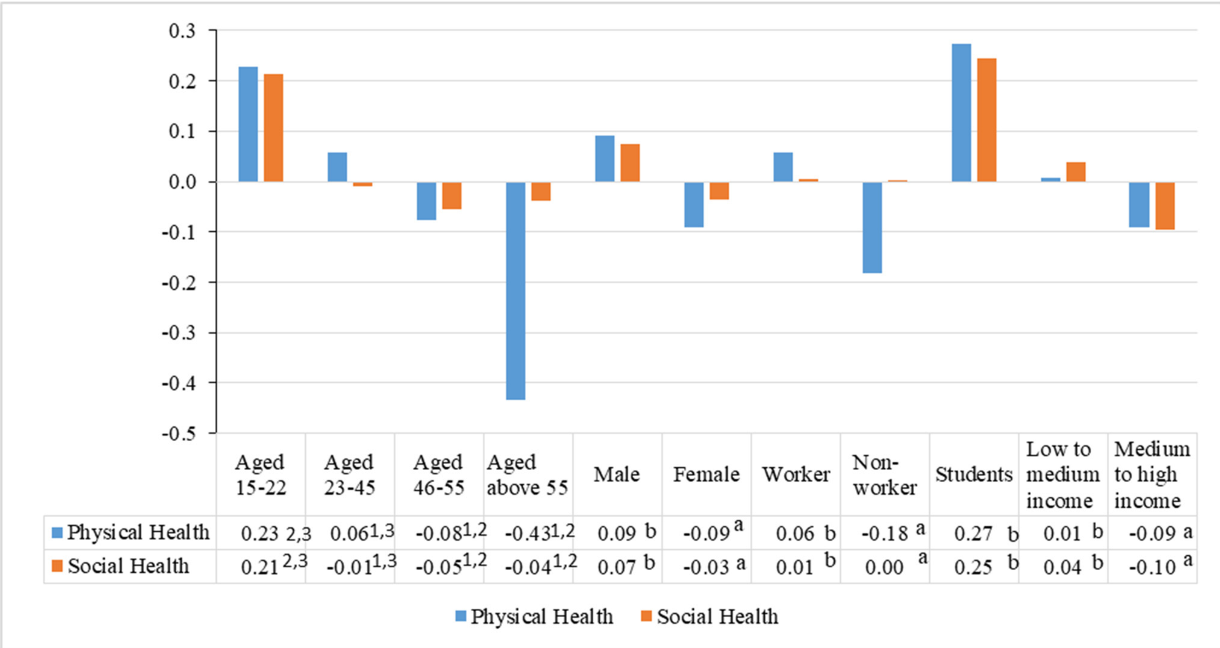

Figure 6. Health indicators with socio-demographic characteristics. Note: superscripts a and b show distinct group means with a *p*-value < 0.1, while (1,2) items show significant mean differences between the young person and elderly citizen group means with a *p*-value < 0.1. Furthermore, (1,3) show a significant difference in averages between elderly citizens and persons in the productive age group (*p*-value < 0.1). Superscripts (2,3) show a significant difference in averages between the group of young people and persons in the productive age range (*p*-value < 0.1).

4.3. Model Estimation Results

The statistical analysis was conducted based on the proposed theoretical model as depicted in Figure 7, in which the right-side variables (outside the box) represent the independent/exogenous variables, whereas the variables inside the box depict intermediate and endogenous variables. The independent variables, such as gender, age, income, household characteristics, occupation, marital status, and education level, are categorical. For instance, gender was categorized as male/female, whereas the occupation was categorized as worker/non-worker/student, etc. Five different models were constructed in which socio-demographic and economic variables were treated as exogenous variables where NMT was treated as an endogenous variable in the first model, MT was the dependent variable in the second model, and PT was treated as an endogenous variable in the third model. In the fourth and fifth models, the output or response variables were the health parameters (PH and SH), whereas all three transport options were used as intermediate variables, and the socio-demographic and economic variables were treated as input variables. The TM was employed as a mediation variable to find the correlation and effect of socio-demographic dependency on urban mobility on PH and SH. Based on the theoretical models, mathematical equations are proposed as shown in Equations (3)–(7).

In this model, the individual daily ATP variation made by the individual "i" household "h" on a day "t" is regarded as the coefficient parameter (βn). Yet, the mean of the individual's uncorrelated and particular error term (ui) was zero. The εi,t, on the other hand, had a mean value of zero and represented the uncorrelated individual and temporal error components. The following equations were proposed to describe the proposed model of socio-demographic dependency on urban mobility well, TM, and its influence on health parameters. The income I has a subscript h, which shows the household income.

$$\textbf{(Motorized transport)}_{\mathbf{i,h,t}} = (\alpha_{i,h} + u_i + u_h) + \beta_1\, G_i + \beta_2\, A_i + \beta_3\, I_{i,h} + \beta_4\, H_h + \beta_5\, O_i + \beta_6\, M_i + \beta_7\, edu_i + \varepsilon_{i,h,t} \quad (3)$$

$$\textbf{(Non-motorized transport)}_{\mathbf{i,h,t}} = (\alpha_i + u_i + u_h) + \beta_8\, G_i + \beta_9\, A_i + \beta_{10}\, I_{i,h} + \beta_{11}\, H_h + \beta_{12}\, O_i + \beta_{13}\, M_i + \beta_{14}\, edu_i + \varepsilon_{i,h,t} \tag{4}$$

$$\textbf{(Public transport)}_{\mathbf{i,h,t}} = (\alpha_i + u_i + u_h) + \beta_{15}\, G_i + \beta_{16}\, A_i + \beta_{17}\, I_{i,h} + \beta_{18}\, H_h + \beta_{19}\, O_i + \beta_{20}\, M_i + \beta_{21}\, edu_i + \varepsilon_{i,h,t} \tag{5}$$

$$\textbf{(Physical health)}_{\mathbf{i,h}} = (\alpha_i + u_i + u_h) + \beta_{22}\, G_i + \beta_{23}\, A_i + \beta_{24}\, I_{i,h} + \beta_{25}\, H_h + \beta_{26}\, O_i + \beta_{27}\, M_i + \beta_{28}\, edu_i + \gamma_1\, (\text{Motorized transport})_{i,h,t} + \gamma_2 (\text{Non-motorized transport})_{i,h,t} + \gamma_3 (\text{Public transport})_{i,h,t} + \varepsilon_{i,h,t} \tag{6}$$

$$\textbf{(Social health)}_{i,h} = (\alpha i + u_i + u_h) + \beta_{29}\, Gi + \beta_{30}\, A_i + \beta_{31}\, I_{i,h} + \beta_{32}\, H_h + \beta_{33}\, O_i + \beta_{34}\, M_i + \beta_{35}\, edu_i + \gamma_4\, (\text{Motorized transport})_{i,h,t} + \gamma_5\, (\text{non-motorized transport})_{i,h,t} + \gamma_6\, (\text{Public transport})_{i,h,t} + \varepsilon_{i,h,t} \tag{7}$$

In the statistical analysis, the coefficient parameters, such as uncorrelated $\varepsilon_{i,h,t}$, and uncorrelated and specific error terms β_n, u_h, and u_i, are the time error, household, and individual components with a nasty value of null.

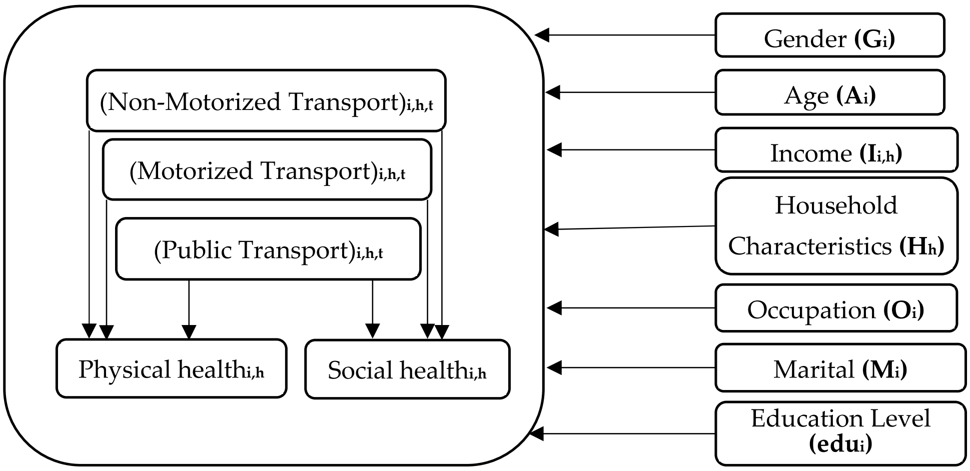

Figure 7. The proposed model.

4.4. ANOVA

Table 4 displays the five distinct models that were produced in response to the five distinct dependent variables. The model's performance was assessed based on the ANOVA tables and the significance with a value of less than 0.05 due to the 95% confidence interval (CI). All five models were statistically significant with a *p*-value below 0.0005. A statistical method for figuring out the dispersion of the data points in a regression study is the sum of squares. A smaller result indicates little deviation from the mean, while a bigger sum of squares suggests higher variability. In the current study, models 2 and 3 show the lowest sum of squares compared to the rest of the models, which show less variability of the data points from the straight line. In addition, the degree of freedom (df) for the regression is the number of predictors in the model, whereas the df for error is the number of observations minus the number of parameters estimated [56]. However, the total df is the number of observations minus 1 [57]. The total number of predictors for the first three models was 20, and in the 4th and 5th models, it was 23 due to the addition of NMT, MT, and PT. Therefore, the df for the regression was 20 for the first three models and 23 for the last two models. The df for the residuals is the number of observations (10,668) minus the number of parameters estimated (20); therefore, it was 10,648. However, the total df is the total number of observations minus 1 which is 10,668 − 1 = 10,667.

Table 4. ANOVA.

ANOVA					
Model_1 [a] (dependent variable: Motorized Transport Mode)					
Statistics	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Regression	183.978	20	9.199	43.924	0.000 [b]
Residual	2229.539	10,648	0.209	-	-
Total	2413.516	10,667	-	-	-
Model_2 [c] (dependent variable: Non-Motorized Transport Mode)					
Regression	46.463	20	2.323	13.423	0.000 [b]
Residual	1842.497	10,648	0.173	-	-
Total	1888.96	10,667	-	-	-
Model_3 [d] (dependent variable: Public Transport Mode)					
Regression	11.104	20	0.555	8.006	0.000 [b]
Residual	738.22	10,648	0.069	-	-
Total	749.323	10,667	-	-	-
Model_4 [e] (dependent variable: Physical Health)					
Regression	172.568	23	7.503	32.543	0.000 [b]
Residual	2453.778	10,645	0.231	-	-
Total	2626.346	10,667	-	-	-
Model_5 [f] (dependent variable: Social Health)					
Regression	128.119	23	5.570	23.613	0.000 [b]
Residual	2540.735	10,645	0.236	-	-
Total	2638.854	10,667	-	-	-

Note: [a] dependent variable: motorized transport mode; [b] predictors: (Constant), No_Edu, worker, Divorced, High Income, Master_PhD, Cohabiting, D_CHILD, Bachelor, Diploma, Below 55, Above 55, Elementary, Male, Single, Low Income, Jounier, Below 22, HH_MEMBER, Student, Below 45; [c] dependent variable: Non-Motorized Transport Mode; [d] dependent variable: Public Transport Mode; [e] dependent variable: Physical Health; [f] dependent variable: Social Health.

4.5. R Studio Analysis

Table 5 depicts the model estimation results using Linear and non-linear Mixed Effect (NLME) models, Multi-Level (ML), and Structural Equation Modeling (SEM) between exogenous variables, intermediate variables, and response variables. The findings are generated using a 2-stage least square (2SLS) using instrumental variable (IV), NLME, and ML regression analysis in R-Studio based on a standardized value to measure the impact of exogenous factors on the endogenous variables, represented in negative and positive signs. The IV is widely used to solve the endogeneity issues in the SEM [58]. The estimation results show that TM significantly mediates the relationship between socio-demographic and economic variables and health parameters.

Regarding gender, female is used as a reference variable for males, while non-workers are for workers and students in occupations. In addition, those over 55 years of age are used as a reference for the rest of the ages and cohabiting for the marital status in the statistical analysis. Based on the outcomes, a positive correlation was found between MT and males, whereas NMT and PT were the opposite; therefore, a high dependency on MT for daily activities is negatively associated with PH. However, there was an insignificant correlation between TM and SH. As suggested by the previous studies, males engage in more IH and OH activities, which improve their health parameters; however, car-dominant is negatively associated with health outcomes [59]. The current study claims that using different TMs (especially MT) while engaging in a diverse set of daily activities is negatively correlated with PH, while no such association is found with SH.

Table 5. Model estimation result for NMT, MT, PT, PH, and SH.

Factors	Non-Motorized Transport		Motorized Transport		Public Transport		Physical Health		Social Health	
	Coeff	T-Statt	Coeff	T-Statt	Coeff	T-Statt	Coeff	T-Statt	Coeff	T-Statt
Constant values	0.513	11.343	0.193	3.981	0.049	1.680	0.591	11.08	0.648	12.04
					Socio-demographic characteristic					
Gender										
Male	−0.43	−4.146	0.146	14.301	−0.085	−8.073	−0.056	−5.405	-	-
Female					Ref					
Occupation										
Worker	−0.054	−4.473	0.129	10.948	0.119	9.842	−0.019 *	−1.616	-	-
Student	−0.081	−5.616	0.152	10.858	0.042	2.924	-	-	0.049 *	2.43
Non-worker					Ref					
Ages										
Below 22	0.09 *	3.302	-	-	-	-	0.321	14.83	0.180	8.20
Below 45	−0.171	−3.729	0.152	3.388	-	-	−0.312	−18.26	0.152	8.80
Below 55	0.090	2.742	−0.109	−3.391	-	-	0.281	14.59	0.125	6.39
Above 55 years					Ref					
Household Income										
T20 (>6 million)	−0.045	−4.371	0.029	2.931	−0.026	−2.512	−0.148	−4.83	0.051	1.65
B40 (<3 M IDR)	0.043	4.191	0.04	3.944	−0.025	−2.366	0.055	4.527	-	-
M40 (3–6 M IDR)					Ref					
Household Characteristics										
Number of family memberships	0.024	2.143	−0.022	−2.018	0.025	2.247	−0.033	−9.903	−0.050	−14.73
Number of Reliant kids per family	−0.046	−4.032	0.030	2.669	−0.018	−1.555	−0.015	−2.695	−0.039	−6.81
Marital Status										
Married	-	-	0.099	2.398	-	-	−0.22	−4.69	-	-
Single	−0.032	−3.073	-	-	−0.032	−3.073	0.23	4.89	0.085	1.75
Divorced	-	-	−0.039	−4.031	-	-	−0.25	−4.77	−0.09 *	−1.67
Cohabiting					Ref					
Education Level										
Elementary School	−0.021	−2.021	0.016 *	1.545	0.019 *	1.849	−0.041	−2.849	0.058	3.99
High School	-	-	-	-	0.030	2.865	-	-	0.076	5.51
Junior School					Reference					
Diploma	0.021 *	2.037	−0.048	−4.838	0.022 *	2.168	0.022	2.381	0.018	3.291
Bachelor	0.050	4.896	−0.061	−6.188	0.012	1.202	0.066	4.05	0.05	3.38
Master_PhD	0.047	4.715	−0.02 *	−2.390	0.002	0.185	0.11	4.65	-	-
No Education	-	-	-	-	-	-	−0.07	−3.62	0.042	1.95
Endogenous of Non -Motorized	-		-		-		0.035 *	2.31	−0.03	−2.35
Endogenous Motorized	-		-		-		−0.065	−0.42	−0.004	−0.30
Endogenous Public	-		-		-		0.021 *	0.345	0.014	0.683
Statistical Terms										
Individual specific Error term (u_i)	0.255		0.366		0.0426		0.4789		0.4857	
The term "independent random error" (ε_i)	0.0647		0.0581		0.0366		0.0534		0.0538	
Standard error of estimate	0.458		0.416		0.263		0.480		0.486	
R^2	0.214		0.209		0.224		0.256		0.220	
Degree of Freedom (df)	20		20		20		23		23	
AIC	13,561.51		11,561.9		1836.248		14,634.86		14,918.94	
BIC	13,728.83		11,729.23		1981.746		14,816.74		15,100.82	
Loglik	−6757.756		−5757.952		−898.1238		−7292.431		−7434.472	

Note: "-" shows insignificant values, "Ref" shows the reference variable, "*" shows a *p*-value below 0.01, while all other *p*-values were below 0.05.

In terms of occupation, both workers and students have a negative correlation with NMT while having a positive association with MT and PT. Workers are 0.129 (12.9%) and

0.119 (11.9%) positively associated with MT and PT while having a 0.019 (1.9%) negative correlation with PH and no such correlation with SH. Students are 0.152 (15.2%) and 0.042 (4.2%) positively associated with MT and PT while having no such association with PH, but due to participation in social activities, it is 0.049 (4.9%) positively correlated with SH. In addition, students engage in more PT in which they have social interactions and perform multitasking activities; therefore, participating in social activities using PT can 4.9% positively enhance their SH. As suggested by recent and past studies, those who use PT and perform multitasking activities have better SH [18,60].

The current study shows that high-income (T20) households are more involved in different mandatory and discretionary activities at different places and are highly car-dominant while those from low-medium income (B40) use NMT and PT. Therefore, the high-income household shows a negative correlation with NMT and PT and a positive correlation with MT. Those from high-income households are 0.029 (2.9%) positively associated with MT, which is 0.148 (14.8%) negatively associated with PH. However, participation in several activities with different groups of people enhances their PH. Therefore, the current study professes that high-income households are 0.051 (5.1%) positively associated with SH. As suggested by recent and past studies, car-dominant daily activities are negatively associated with the PH [61]. The current study confirms that those who are from high-income households are more dependent on the MT mode, which negatively influences their PH. In addition, the latest literature shows that engaging in several social activities improves SH [62].

Due to the low-income households and developing countries, those below 22 years are highly dependent on NMT which shows a 0.09 (9%) positive association with NMT, 0.321 (32.1%) with PH, and 0.018 (18%) with SH. Those aged 23–45 years are highly car-dependent, which shows a 0.152 (15.2%) positive correlation with MT, but 0.312 (31.2%) negatively associated with PH and 0.152 (15.2%) positively correlated with SH due to participation in several out-of-home-activities. In addition, those who are under 55 years old have a positive correlation with NMT, which is 0.281 and 0.125 enhanced PH and SH, but have a negative association with MT and have no such correlation with PT. The current study confirms that those who are younger (below 22) and older citizens (55 years) are more willing to use NMT and PT, while young adults (below 45) are car-dependent.

Those household members who are reliant on children in their home are negatively associated with NMT and PT but oppositely associated with MT, which negatively influences their PH and SH. As suggested by Ali et al., those households that have dependent children in their house are positively associated with PH and SH [63]. In addition, McCarthy et al. concluded that dependent children in a household influence the transport mode choice and encourage travel by car when traveling with young children [64]. The current claims that those household members who have a dependent child in their household are 0.030 (3%) positively associated with MT, which is 0.015 (1.5%) and 0.039 (3.9%) negatively associated with PH and SH.

There is a statistically significant correlation between health parameters and TM. NMT shows a positive association with PH and a negative correlation with SH, whereas MT is negatively associated and PT is positively correlated with both PH and SH. Increasing the number of people who walk, bike, and take the bus to get around is a popular goal in modern transportation policy because it can simultaneously reduce traffic and improve public health [65–67]. The current study is in line with recent and past studies that show that using the MT mode for daily activities can negatively influence health parameters [68–70]. A unit increase in the NMT mode is 0.035 (3.5%) positively correlated with PH. As suggested by Dharmowijoyo and Joewono, participating in an activity-travel pattern using the NMT mode is positively associated with PH [15]. Additionally, a study by Lumsdon and Mitchell in the UK on traffic reduction and health promotion by promoting walking for better health concluded that more research has to be performed into planning for walking as a method of transportation [71]. Mansoor et al. 2022 studied the factors and benefits of the NMT mode and concluded that it reduces traffic congestion and improves physical and mental health [72].

5. Conclusions and Recommendations

The current study aims to study the influence of TU and ATP on health parameters by utilizing transport modes as an intermediate variable. Based on the statistical analysis and model estimation results, a subsequent conclusion can be drawn.

- The current study claims that there is a significant association among the exogenous, intermediate, and endogenous variables with an exceptionally strong range of R^2 values. In addition, it was found that all three transport modes, such as MT, NMT, and PT, mediate the relationship between TU and ATP and health parameters. The outcome of the current study shows that shifting urban dependency from private vehicles towards NMT or PT is positively associated with health parameters.
- Using MT to participate in an activity is negatively associated with both PH and SH; therefore, a unit increase in MT is 6.5% and 4% is negatively associated with PH and SH. However, using PT to participate in an activity is the opposite, where a unit increase in the daily use of PT is 2.1%, and 1.4% is positively associated with PH and SH.
- In addition, NMT has a positive correlation with PH and a negative association with SH in which a unit increase in the NMT mode 3.5% positively affects PH and 3% negatively affects SH. The positive association with PH is due to active transport, while the negative association with SH is due to the individual not participating in social activities while walking or cycling. Therefore, replacing a single journey of a private vehicle with NMT and PT 3.5% and 2.1% positively influences PH, whereas PT offers substantial SH benefits for multitasking activities; therefore, choosing PT over a private vehicle positively enhances SH by 1.4%.
- TMC prediction is crucial for urban planners and policymakers to study travel behaviors, which enables them to anticipate and influence how people move within a city and how they react to the available transport options. The prediction of TMC has several practical implications, such as infrastructure planning, a reduction of traffic congestion, equity in mobility, economic efficiency, environmental benefits, and health promotion. Therefore, the current study helps policymakers and urban planners develop the infrastructure and transportation system based on the needs and demands or utilize the demands in the available infrastructure and promote a sustainable transportation system.

The current study utilized conventional techniques, such as logit models, R programming for statistical analysis, and SPSS for descriptive statistics, whereas it utilized Pearsons's correlation for the classification of different transport modes. However, these conventional techniques are mostly based on assumptions and create bias in the analysis. Therefore, it is strongly recommended to utilize modern techniques, such as artificial intelligence and machine learning techniques to study the correlation between socio-demographic and economic variables, determinants of TMC, health parameters, and GHG emissions.

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Informed Consent Statement: Respondents declared their consent to inclusion in the survey and completed the survey while supervised by the community leaders and surveyors.

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