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The spatiotemporal variable effects of individuals' CO_2 emission in Bandung Metropolitan Areas

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ABSTRACT

Many investigations have been using disaggregated measurements to estimate individuals' CO_2 from road passenger transport, especially in developed countries. Nevertheless, similar investigation in developing countries emphasized their focus on aggregate measurements and system dynamics. There is a lack of disaggregated measurement in developing countries, particularly in Indonesia, and how the effects of spatiotemporal variables such as socio-demographic, travel parameters, and activity pattern variables correspond with CO_2 estimations. Since Indonesia is dominated by motorcycle users, this study will show motorcycles' contribution to CO_2 emissions. The results of 2.23 kg-CO_2 per day of individuals' CO_2 emissions in Indonesia is quite low in comparison to results in some developed countries such as the Netherlands and Sweden. It is presumably because around 86.05% of individuals in the observations used private motorcycles to travel and a low number of the undertaken trip in the BMA (Bandung Metropolitan Area). Around 91.39% of CO_2 emissions were emitted by individuals who take 80% of using private motorcycles and cars. This study shows that the disaggregated modeling on estimating CO_2 emissions might be able to reveal which individuals can be targeted to reduce their CO_2 emissions and what can be done to help government policy in reducing CO2. Female part-timer workers, female non-workers, and senior citizens are those who show the lowest contributions to CO_2, and providing acknowledgments might make them keep such achievements. Whose daily travel time is below 106 and 125 minutes might be clustered as the targeted group of individuals that can reduce their CO_2 production. Incentive schemes such as providing internet vouchers or vouchers to use ride-hailing might help to change their habits to shift some of their trips by taking non-motorized mode, public transport, and/or ride-hailing services. Keeping public amenities at a farther distance might reduce people increase trips and travels by using motorized mode. But increasing the distance might make effects social exclusion, in turn, social health.

Keywords : individuals' CO_2 estimation, spatiotemporal variables, disaggregate measurements, infrastructures, and facility asset management.

INTRODUCTION

Air pollution in the urban area can be very serious. Urban transportation is the main contributor to urban air pollution. In general, the main solution to this problem is vehicle pollution reduction regulation. But, urban infrastructure and facilities must participate also in air pollution reduction. Thus, infrastructure and facilities need to be well planned, designed, constructed, operated, and maintained to participate in pollution reduction. (Suprayitno & Soemitro, 2018).

The highest contributors of Green House Gases (GHG) in transport sectors are CO_2 with 97%, whereas hydrofluorocarbons (HFCs), nitrous oxide (N_2O), and methane (CH_4) emit around 2.1%, 0.8%, and 0.1%, respectively (EPA, 2019). The transport sector has become the second biggest contributor to CO_2 emissions after the power industry sector in the world and northern hemisphere countries (PBL Netherlands Environmental Assessment Agency, 2016). In some countries, transport sectors have produced CO_2 emissions greater than the power industry and other combustion industries. In 2005, CO_2 of transport sectors in Indonesia contributed 25% of total CO_2 emissions which made the sector the third largest emitter below the power industry and other combustion industrial sectors (each sector contributed 29%, Worldometers, 2020). In 2006, the transport sector contributed 27% of total CO_2 and exceeded the contributions of other combustion industrial sectors. Ninety-one percent of CO_2 of transport is contributed by road transport, whilst only 1% and 8% are contributed by marine and air transportation, respectively (ESDM, 2012; Sukarno et al., 2016). Around 60% of the CO_2 of road transport is from passenger transport, whilst the rest is from freight transport (ITF Outlook, 2017, EPA, 2019). Furthermore, passenger transport will be dominated by short-distance travel in dense areas as in urban areas. (ITF Outlook, 2017). Therefore, the focus of reducing GHG in transport will be on reducing the CO_2 of passenger and urban transport.

Research on reducing CO_2 emissions from the transport sector in Indonesia, mostly, was conducted using aggregate measurements (Saputra et al., 2017; Deendarlianto et al., 2020; Setiawan et al., 2021) and system dynamics (Sukarno et al., 2016). In deriving the CO_2 in transport, CO_2 emissions are estimated by the aggregating yearly average number of trips, yearly average vehicle km travel, and total travel time per year. The aggregate measurement method only focuses on a strategy of changing the fuel types, vehicle technology, and mode choice. However, there is a trend that the CO_2 production from the transport sector has substantially grown in many regions from time to time (European Commission. 2015; Rahman et al., 2015). Congestions and shifting travelers to more sustainable transport remain the homework of many governments in developed and developing countries. However, such aggregation contains some weaknesses as they tend to ignore detailed activity-travel patterns that vary by individuals on each day or each season, or in each region. Moreover, the effects of socio-demographics, activity-travel patterns, built environment conditions, and other individuals' characteristics on CO_2 production are also overlooked. Aggregate measurements lack of suggesting a change in people's travel behavior or urban land use and the individuals' target on how people reduce CO_2. Therefore, research in developed countries started to switch to investigating individuals' CO_2 (Susilo and Stead, 2009; Barla et al., 2011; Waygood et al., 2014; Liu et al., 2016) for detailing how the change in behavior and land use can help in reducing $CO_{2.}$

A disaggregated data measurement or individuals' CO_2 estimation is proposed to allow detailed mitigation of CO_2 reductions from road passenger transport, particularly in the urban area. There is a consensus that the understanding of people's travel time and travel distance must also include the interdependency between land use and transport system, the linkages between travels and activities, temporal constraints, and interdependencies among activities of individuals and among individuals (McNally, 2000; Flyvberg et al., 2005) and identifying non-instrumental constraints such as the influence of habit, goal-directed behavior and lifestyle (Dijst et al., 2008; Van Acker et al., 2016) and mobility biography (Lazendorf, 2003; 2010; Chatterjee et al., 2013; Jones et al., 2014; Beige and Axhausen, 2017). Those who have commitments to do more trips or trip chains, in turn, to have a longer travel time tend to be more difficult to shift to more sustainable transportation options (Susilo and Dijst, 2010;

Dharmowijoyo et al., 2016). The understanding can suggest some individuals who are difficult to be targeted in reducing their daily CO_2 production. However, some possible incentives might be able to be proposed to those who have the potential to reduce their CO_2.

Since most individuals' CO_2 research was conducted in developed countries, there is a lack of understanding of the amount of CO_2 emitted by using disaggregation measurements and activity-based analysis in developing countries, particularly in Indonesia. This is the main gap in this study. The availability of national transport surveys, and activity and travel diary data make the CO_2 emission measurement using disaggregated data possible. In addition, since private cars are the main private vehicles used in developed countries, motorcycles are found as the dominant mode in Indonesia. This study might provide another insight into how the reduction of CO_2 can be conducted in a country with high usage of motorcycles. The policy indication suggested in this study might be more interesting since the public transport conditions in Indonesia is poor in comparison to developed countries (Susilo, 2011; Dharmowijoyo et al., 2020). Incentives to target travelers who are the potential in reducing their CO_2 production are hypothesized as one of the policy indications in this study.

ARTEMIS model is frequently used to estimate individuals' CO_2 as it can include the variability of activity-travel patterns between individuals and within individuals on different days (Boulter and McCrae, 2007; Susilo and Stead, 2009; Liu et al., 2016). Therefore, the objective of this study is to estimate the CO_2 total Emission (E_{total}) per trip per individual aggregated into kg-CO_2 emission per person per day using ARTEMIS model. Furthermore, we aim to examine the descriptive analysis of kg-CO_2 emission per day/person breakdown into various spatiotemporal variables such as socio-demographic, travel and activity patterns, and built environment. ARTEMIS model breakdowns the emission models into three components: (1) hot exhaust emission, the amount of CO_2 being emitted during the use of vehicles; (2) cold start emissions, the amount of CO_2 being emitted during each trip start when the engine does not reach its running temperature; and (3) evaporative emissions, the amount of CO_2 emissions due to evaporative losses of volatile organic compounds. Hot exhaust and evaporative emissions include the total travel distance performed by individuals on a given day, whereas cold start emissions consider the total travel time per day of individuals. The estimation, then, is transferred to the daily total CO_2 emissions emitted by an individual. Bandung Metropolitan Area (BMA) 2013 dataset was used since the data was the only available data that contain activity/travel diary. Dharmowijoyo et al. (2015) and Dharmowijoyo (2016) found that motorcycles are used by most travelers in Indonesia on their daily trips using Bandung Metropolitan Area (BMA) 2013 dataset. Therefore, this study is unique since individuals' CO_2 in such developing countries as Indonesia might be dominated by high use of motorcycles rather than high use of private cars. This study does not directly investigate the effects of CO_2 emissions on infrastructure, but it can indicate how pedestrian and cycling networks could be improved to help in reducing CO2 emissions in conjunction with having more diverse land use. Some public transport developments can be also indicated using this study.

In the next section, data sets and ARTEMIS mode specifications will be explained. Sections 4 and 5 describe the general descriptions of individuals' average CO_2 emissions and the variability of people's CO_2 emissions broken down into multiple variables. Section 5 discusses the conclusion and discussions.

Bandung Metropolitan Area (BMA) 2013 dataset

To the author's knowledge, the BMA dataset was the first activity diary survey in developing countries (Dharmowijoyo et al., 2015; Dharmowijoyo, 2016). The data were collected in 2013 that contain detailed day-to-day activity-travel participation, and its duration is for 21 days. Seven hundred and thirty-two individuals from 191 households were included in the survey. Adults and dependent children were part of the respondents. Much multi-dimensional information such as health, physical activity, psychological mechanism, lifestyle, household information, and well-being information was also captured. Therefore, this dataset is not only able to investigate the complexity and variability of individuals' activity-travel behavior, but it is also possible to do children's travel behavior in developing country context.

Inactivity diary data, twenty-three types of in-home and out-of-home activity categorizations have been recorded for 21 days. In the analysis, the activity classification, is then, squeezed into mandatory, maintenance and leisure activities (Meloni et al, 2004; Schwanen et al., 2008). In terms of locations, mandatory, maintenance and leisure activities are categorized into in-home and out-of-home activities. Mandatory activities are defined as activities with higher temporal and spatial fixity when a particular activity is defined to be difficult to re-scheduled (Cullen and Godson, 1975; Meloni et al., 2004; Schwanen et al., 2008) such as working, going to school and pick up/drop activities (Schwanen et al., 2008). Discretionary activities which contain maintenance and leisure are activities with higher temporal and spatial flexibility (Cullen and Godson, 1975; Schwanen et al., 2008). The activities can be easily re-scheduled such as grocery shopping and leisure activities. Maintenance activities tend to be conducted for satisfying household and personal physiological and biological needs (Akar et al., 2011) such as household-related activities, babysitting, health treatment activities, grocery shopping, and other service activities (such as going to the bank, post office, Akar et al., 2011). For this study, out-of-home maintenance activities were separated into grocery shopping and other out-of-home maintenance, whereas household-related activities and babysitting are categorized into in-home maintenance. Moreover, leisure activities are defined as activities undertaken for satisfying cultural and physiological needs such as socializing, entertainment activities, sports, and recreational activities (Akar et al., 2011). For this study, in-home leisure activities were compiled from in-home socializing and in-home leisure (e.g., daydreaming, relaxing, reading newspapers/books/others, watching TV/movies, listening to music/radio), whereas out-of-home leisure activities were divided into out-of-home socializing, out-of-home leisure and recreations, and sports activities.

Land use patterns in BMA and other metropolitans in Indonesia are under constant changes due to leniencies and flexibilities in dealing with market-driven without complying with the original land use and spatial plans. Therefore, digital land use data were not fit to measure the built environment conditions. Consequently, BMA 2013 dataset asked about the perceived accessibility of individuals to various amenities to measure built environment conditions.

Besides that, the dataset also contains GPS location of each activity location. The GPS location can be used to track the travel distance of each trip using a mode of travel. Therefore, the dataset can be used to examine the CO_2 emission production of each trip of everyone within 21 days. In conjunction with the availability of multi-dimensional information captured in this dataset, the CO_2 production of each trip of everyone can be used to analyze bivariate and multivariate relationships between various information such as activity and travel patterns, socio-demographic, attitude, past behavior, health and well-being characteristics of individuals on CO_2 production. The sample profile is shown in Table 1

Table 1. Profile of the samples used in the study

Variables	Percentage of Mean
Socio-demographic characteristics at an individual level:	
Male	52.10%
Worker and non-worker	43.64% and 31.05%[1]
Is a dependent child (<= 14 years old)	12.73%
Age (continuous) (years old)	38.6
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	4.50
Number of dependent children per household	0.80
Number of motorized vehicles per household	1.80
Reside within the inner city boundary of BMA and Greater BMA	44.90% and 37.90%[1]
Daily 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 of using the motorized mode	39.19% (36.77%)
Percentage of using public transport	14.88% (9.55%)
Percentage of using a non-motorized mode	34.49% (32.08%)
Total travel time spent from Monday-Friday (minutes)	74.87(69.35)
Daily time spent on 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 on 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)
Daily percentage of time engaging with multi-tasking activities within certain activities on weekdays (weekends) [2]	
Percentage of time engaging with multi-tasking activities within grocery shopping (*MultiGH*)	17.84% (11.85%)
Percentage of time engaging with multi-tasking activities within travel activities (*MultiT*)	6.89% (5.22%)
Percentage of time engaging with multi-tasking activities within working activities (*MultiW*)	7.11% (3.64%)
Built environment variables[3]*:*	
Km-length of road and railway per square km within the respondents' residential location	38.57 and 4.83
The density of industrial and trade center area per square km within the respondents' residential location	0.0244 and 0.0048
The density of government office and settlement area[4] per square km within the respondents' residential location	0.0120 and 0.4836
Perceived accessibility variables	
Perceived number of public transport lanes passing respondent's resident	2.57
Perceived travel time to CBD and shopping center area (minutes)	31.27 and 15.85
Perceived travel time to the grocery store and park (minutes)	8.34 and 18.29
Perceived travel time to the nearest place to stop public transport (minutes)	14.50
Individuals' daily experience/satisfaction (DE)	5.12

Note: A trip chain is defined as home to home trip.

[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 are on weekdays

[3] The density is calculated based on a built area in only a horizontal plane in km^2 divided by the total area in km^2. The measurement excluded the area on the vertical plane

[4] Following the definition of density of a certain built area, living in a denser settlement area does not always mean living in a populated area. The more populous area can mean an area that contains a low-density settlement area in a horizontal plane (but denser in a vertical plane).

The ARTEMIS model

Three types of private vehicle emissions in the ARTEMIS model are hot exhaust emissions (E_h), cold start emissions (E_c), and evaporative emissions (E_e), Boulter and McCrae, 2007; Liu et al., 2016). The emission factor of running hot exhaust emissions (F_h)

was estimated using average speed functions as factors of type of roads, traffic conditions, engine capacity, type and legislative category (whether the engine complies with Euro I-IV or Pre-Euro legislation), type of fuel (petrol or diesel), emission standard of the vehicles, and ambient temperature of the outside vehicle. The emission factor of hot exhaust emissions from the auxiliary system (F_a) depends on the time of the day, ambient temperature outside the vehicle, and weather conditions. F_c or the emission factor of cold start emission is estimated based on engine capacity, type, legislative category, fuel type, emissions standard of the vehicle, ambient temperature outside vehicles, and average speed. This study only considered the running loss of the evaporative emissions (F_e). Road type, weather, and fuel type will classify the determinants of F_e. Since the paper is using the dataset from a tropical country, Indonesia, the weather was assumed not to be significant to influence the emissions factors, thus the effects of weather were disregarded. The engine legislative category was assumed to be still at Pre-Euro legislation. It is presumably because many operated private vehicles were found to still use Pre-Euro legislation. ARTEMIS model concludes the estimation of total Emission of a trip as follows:

$$E_{total} = E_h + E_a + E_c + E_e = F_h \text{ x } D + F_a \text{ x } H + F_c + F_e \text{ x } D \qquad \ldots(1)$$

Where :

E_{total} = *Total Emission of a trip*
E_h = Hot exhaust emissions
E_a = Auxiliary system emissions
E_c = Cold start emissions
E_e = Evaporative emissions
F_h = Emission factor of running hot exhaust emission
F_a = Emission factor of auxiliary system emission
F_c = Emission factor of cold start emission
F_e = Emission factor of evaporative emissions
D = Travel distance of the given trip
H = Travel Time on the given trip

D refers to the travel distance of the given trip, whereas *H* is the travel time of the given trip. The total emission per day of an individual will be estimated by the sum of the total emissions of all trips using private vehicles. Only 77 individuals in the dataset have access to private cars whereas the rest only have access to private motorcycles. Therefore, the individuals' CO_2 estimation is expected to be dominated by the high use of private motorcycles. Those who have access to private cars and motorcycles might shift to public transport or non-motorized mode on different days. Any efforts to take non-motorized transport will not be accounted to emit CO_2. However, in this estimation, those who take public transport will not be assumed to directly emit CO_2. The CO_2 of those who take public transport is assumed to be emitted by public transport providers who are not part of this study.

From the ARTEMIS model, it is found that, on average, 2.23 kg of CO_2 per individual per day was emitted in BMA during observation. The result is comparatively quite low compared to developed countries of 3.80 kg of CO_2 per individual per day based on the 2005 Dutch National Travel Survey (Susilo and Stead, 2009), and the Swedish National Survey of 3.87 kg of CO_2 per individual per day (Liu et al., 2016). It is presumably because around 86.05% of individuals in the observations used private motorcycles to travel, whereas only 13.95% used private cars. The low emitted CO_2 from motorcycles made the CO_2 estimations in BMA lower than estimations in developed countries. Moreover, the number of undertaken trips in the BMA is only 2.51 trips/day/individuals. It means that the average individuals in BMA only did the main trips either for working or for main non-working trips (e.g., grocery shopping trips or pick up/drop child trips) and return home. On average, discretionary trips were not as extensive as in developed countries.

Figure 1 shows that cold and hot emissions from the auxiliary system only account for 4.15% of the average kg-CO_2 emission per day per person, whereas hot running emissions accounted for around 95.85% of the total CO_2 emissions. In a developed country, like Sweden, cold and hot emissions from auxiliary systems contributed 10% of total daily individuals' emissions (Liu et al., 2016) or much higher than in this study. This is presumably because of a lower average number of trips/day and vehicle usage in terms of km-travel/day and total travel time/day in developing countries (Dharmowijoyo and Joewono, 2020).

Figure 2 shows that around 91.39% of CO_2 emissions were emitted by individuals who take more than 80% of using private motorcycles and cars. We found from the database, the highest emitters comprised only 43.90% of our sample, whereas 48.21% of the sample only emitted 1.7% of CO_2 due to the high involvement in non-motorized mode. Figures 3 and 4 show the average CO_2 emission per individual is dropped on weekend days, particularly Sundays due to the reduction of individuals' out-of-home activities and travels on a corresponding day. Such figures reach the highest on Monday.

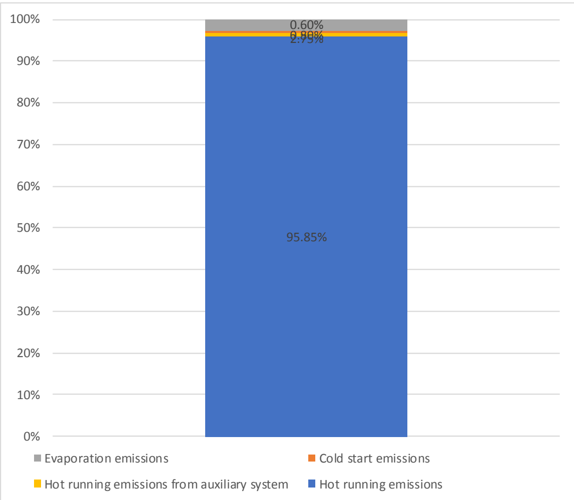

Figure 1. The breakdown of the average Kg- CO_2 emission per day per individual by different types of emitters in road transport

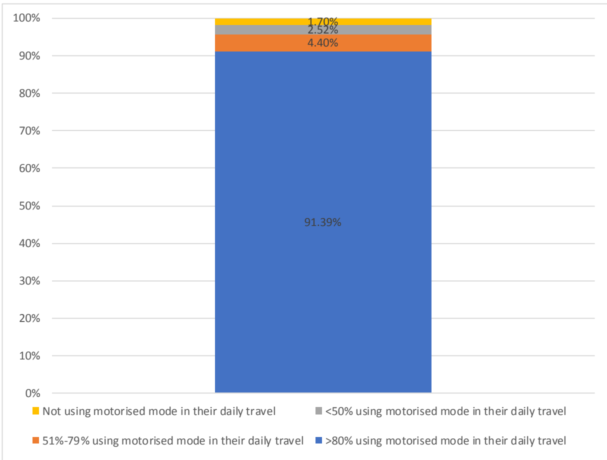

Figure 2. The average Kg- CO_2 emission per day per individual is broken down by different percentages of motorized mode use

The variability effect of socio-demographic, activity-travel patterns, built environment, health and well-being characteristics on CO_2 emissions.

This section tries to break down CO_2 emissions as effects of multiple spatiotemporal variables. Multiple spatiotemporal variables can explain the variability of day-to-day travel distance and travel time (Hägerstrand, 1970; Van Acker et al., 2010; Ellegård and Svedin, 2012; Dharmowijoyo et al., 2016, 2018; Verma et al., 2021). which correspond with individuals' daily CO_2 production.

Figure 5 shows differing CO_2 based on socio-demographic variables such as gender, age, household size, and income. Young male travelers below 22 years old and male travelers between 46-55 years old with higher household members from middle- and high-income households tend to emit higher CO_2. This finding corroborates the existing body of literature that highlighted higher traveling intensity among households with larger members (Kang and Scott, 2010, Liu et al., 2018; Dharmowijoyo et al., 2021a). In developing country case, women and senior citizens are often associated with non-workers with much lower travel production (Dharmowijoyo et al., 2017, 2018, 2020; Manoj and Verma, 2016; Liu et al., 2018; Verma et al., 2021).

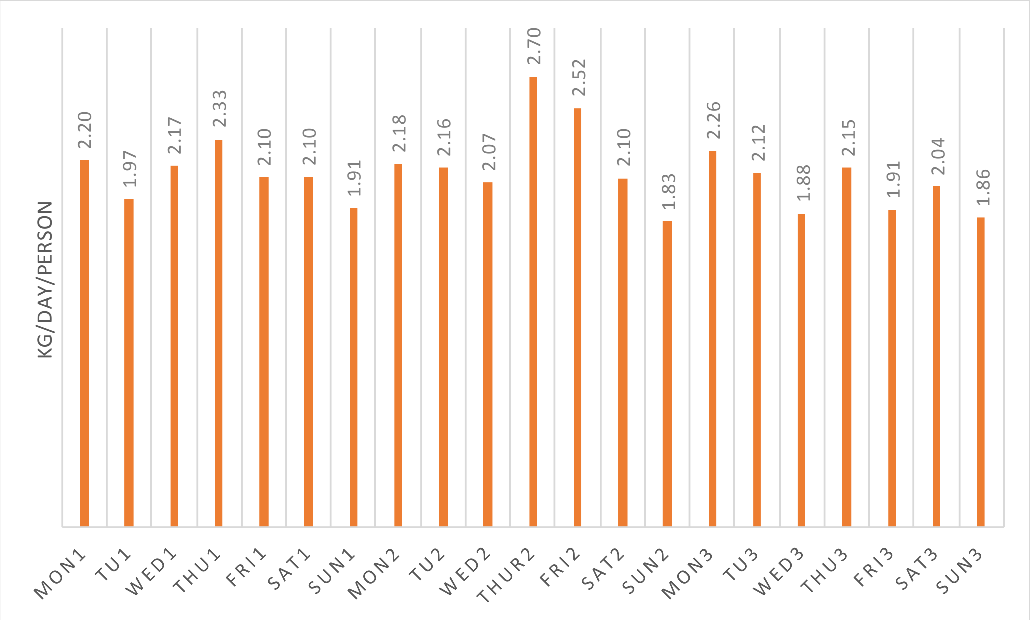

Figure 3. The 21-day variability of the average Kg- CO_2 emission per individual

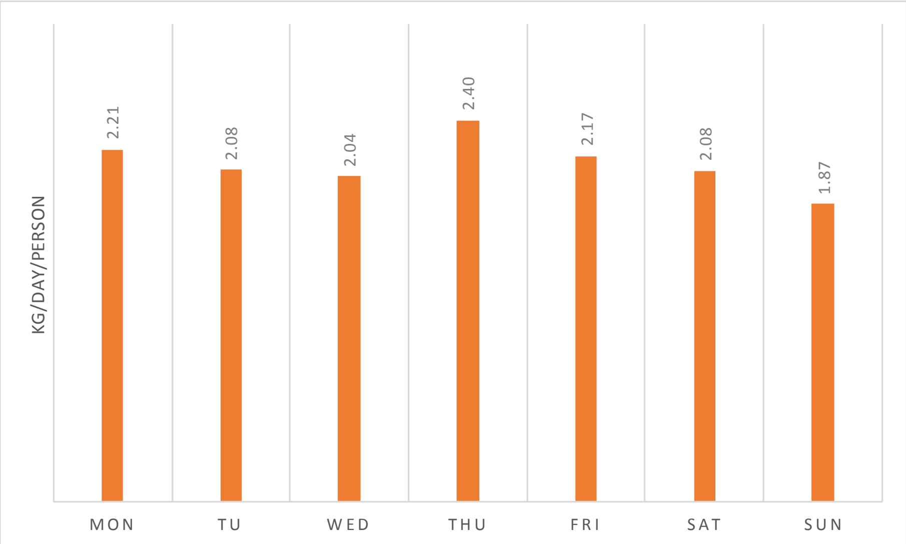

Figure 4. The daily variability of the average Kg- CO_2 emission per individual

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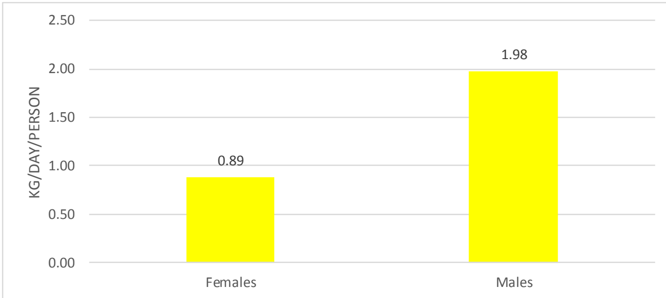
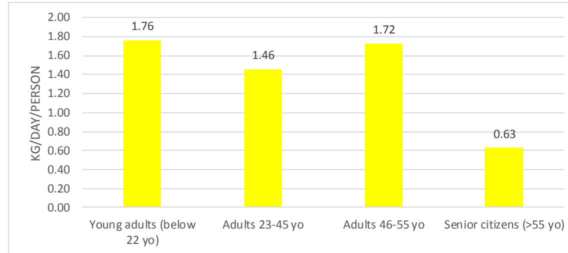
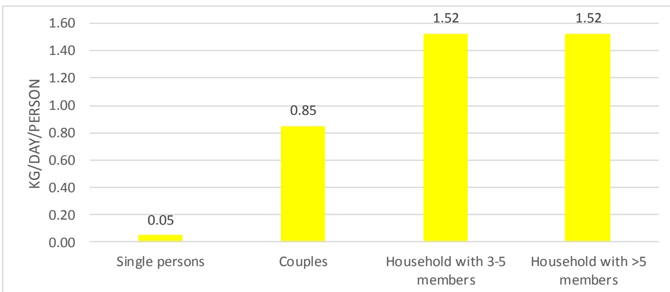
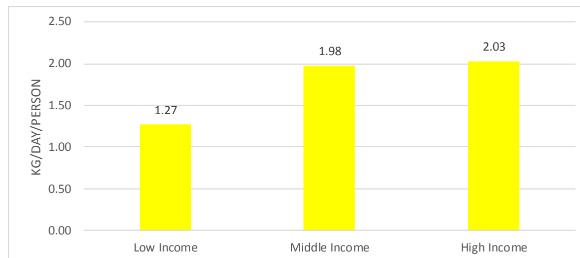




(a) Gender (b) Age





(c) Household members (d) Income

Figure 5. The average kg-CO_2 emission per day per individual broken down into different socio-demographic characteristics

Figure 6 shows that travelers taking more than 80% of private vehicle use per day tend to emit the highest CO_2 emissions per person per day. Reducing the dependency on motorized mode show a tendency of reducing CO_2 production per day and the ones who undertake no motorized mode use tend to emit the lowest CO_2 emissions per day. CO_2 emissions per person per day are exacerbated when individuals have more travel productions. The increase of undertaken trips and trip chains, and the longer performed travel time during the given days correspond with higher CO2. More travel productions might correspond with farther average km of travel distance and longer average travel time as shown in Figure 7 which may associate with higher CO_2 production. In Figure 7, it is shown that people who take motorized mode more often are found not to take longer average travel time per day but take farther average km of travel distance per day. That makes why hot running emissions in this study contribute much higher than the study in developed countries as argued by Liu et al. (2016). The Motorised mode might be chosen to reduce daily total travel time to reach farther distance activity locations per day.

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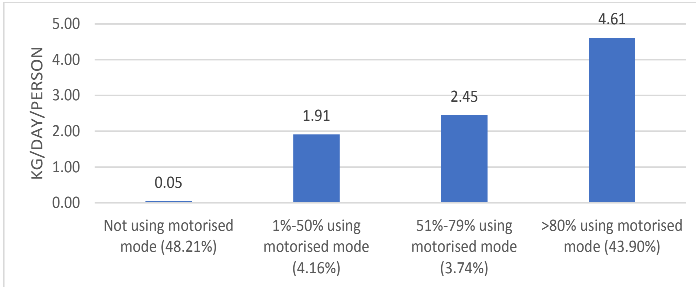
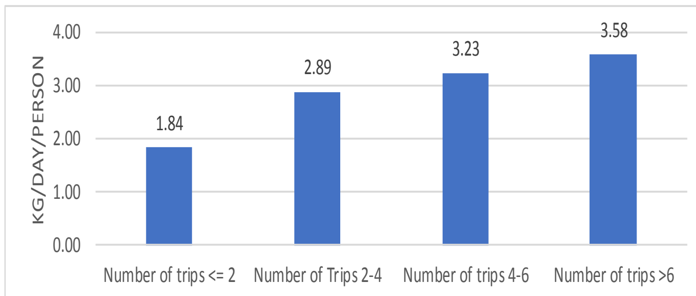
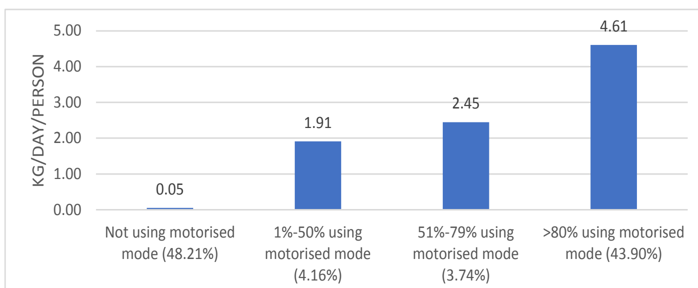


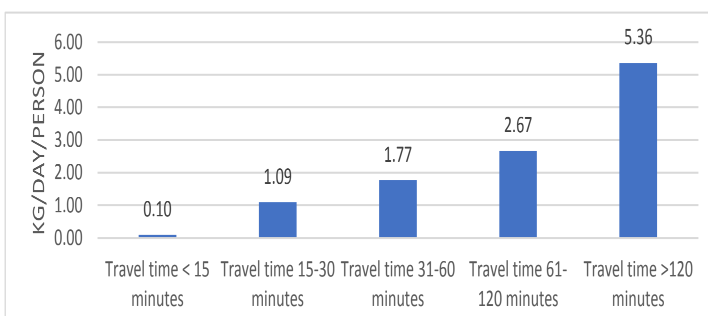
(a) Travel mode



(b) Number of trips per day

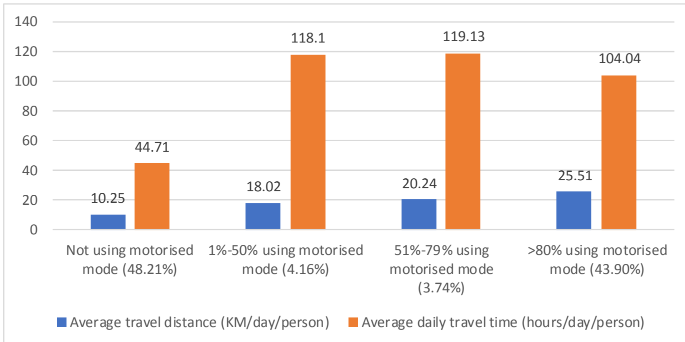


(c) Travel mode

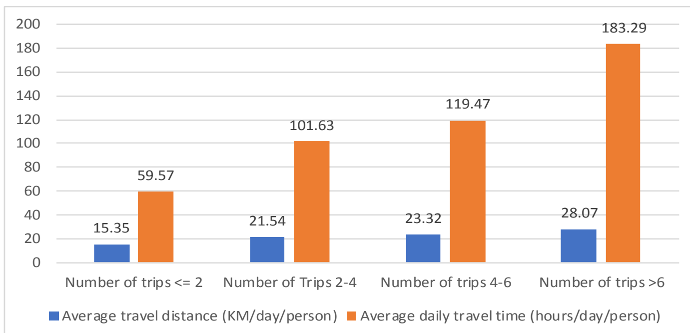


(d) Total travel time per day

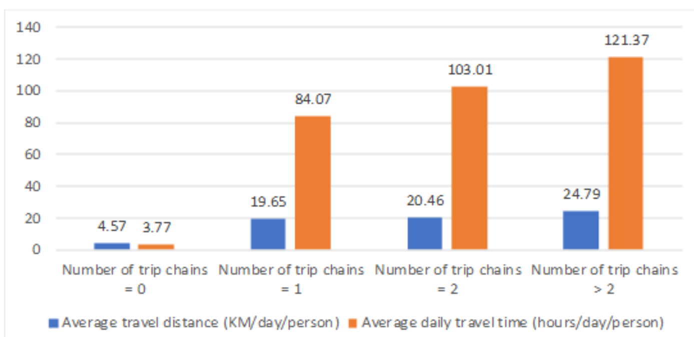
Figure 6. The variability of the average Kg- CO_2 emission per individual by the different travel pattern Characteristics



(a) Travel mode



(b) Number of trips per day



(c) Number of trip chains per day

Figure 7. The variability of travel distance and travel time per individual by different travel pattern characteristics

Figures 8 and 9 show how the combination of some trips and travel modes can describe the effect of travel parameters on daily travel distance and travel time per individual, and daily emissions per individual. The results of Figure 8 are confirmed by Figure 9. Those who contribute to the highest CO2 emissions are those who take private vehicles for more than 80% of their daily travel and take above 6 daily trips. These people are those who travel farthest and longest as shown in Figure 9. Figure 9 also exhibits how the ones who take private vehicles lower than 50% per day and take the number of trips equal to/lower than 2 tend to have farther daily travel distance on average than the ones who use private vehicles lower than 50% and some trips more than 2 (> 2). That might be a reason why in Figure 8 travelers with less than 50% of dependency on private vehicles and some trips equal to/less than 2 tend to emit higher CO_2 than travelers who take some trips more than 2 and with the same dependency level on motorized mode. It seems that travelers who take trips more than 2 and motorized modes lower than 50% might have more commitments within a closer distance from their residential locations. Figure 9 also confirms that travelers who take some trips more than 2 and have more than 80% of dependency on private vehicles in their daily travel time tend to travel farther and longer than people who take some trips more than 2 and take less than 80% of private vehicle use on their daily travel. That might be a reason why those who use more than 80% of a private vehicle on a day and undertake more trips per day tend to have the highest emitted CO_2 per day per person confirmed by Figure 8.

Residential locations have been shown to correlate with activity-travel patterns (Susilo and Maat, 2007; Ewing and Cervero, 2010; Van Acker et al., 2010; Dharmowijoyo et al., 2021b). Travel distance and travel time tend to be higher when people reside in suburban or greater areas (Susilo and Kitamura, 2005; Dharmowijoyo et al., 2014, 2016). Land use diversity is difficult to be determined by whether residential locations are near CBD, in suburban and in the greater area as shown in Table 2 and previous studies (Arifwidodo, 2012; Tarigan et al., 2016; Dharmowijoyo et al., 2021b). Some areas in a greater area particularly in the West part of BMA tend to have higher land use diversity than suburban areas in the East part of BMA as is shown in Table 3. Therefore, areas with more diverse land use are found to have longer travel time, and travel distance as shown in Figure 10, in turn, emit higher CO2 as in Figure 11. Figure 10 and 11 also show due to the farther distance of their residential location to CBD, greater area residents correspond with travel farther and longer on a daily average than the ones staying in CBD and sub-urban areas, which consequently increases CO_2 emission.

In addition, those residing in suburban, CBD, and some greater areas closer to CBD areas as in the west part of BMA tend to have lower travel time (below 20 minutes) to various public amenities. Those conditions make them have higher travel time and travel distance productions as shown in Figure 10 and higher CO_2 emissions as shown in Figure 11. Interestingly, those who reside within areas with shorter travel time than 20 minutes to public amenities correspond with a higher dependency on private vehicles.

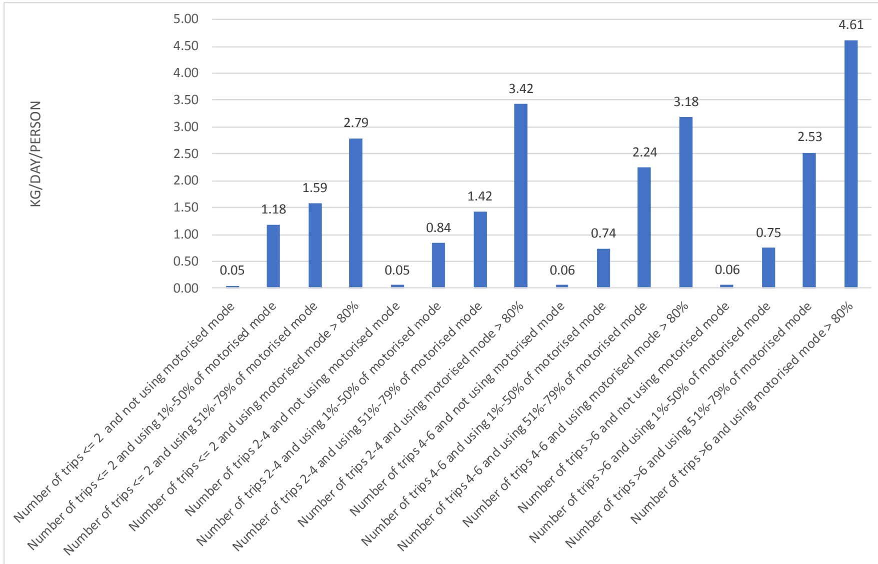


Figure 8. The variability of the average Kg- CO_2 per individual by various combinations of number of trips and percentage of motorized use

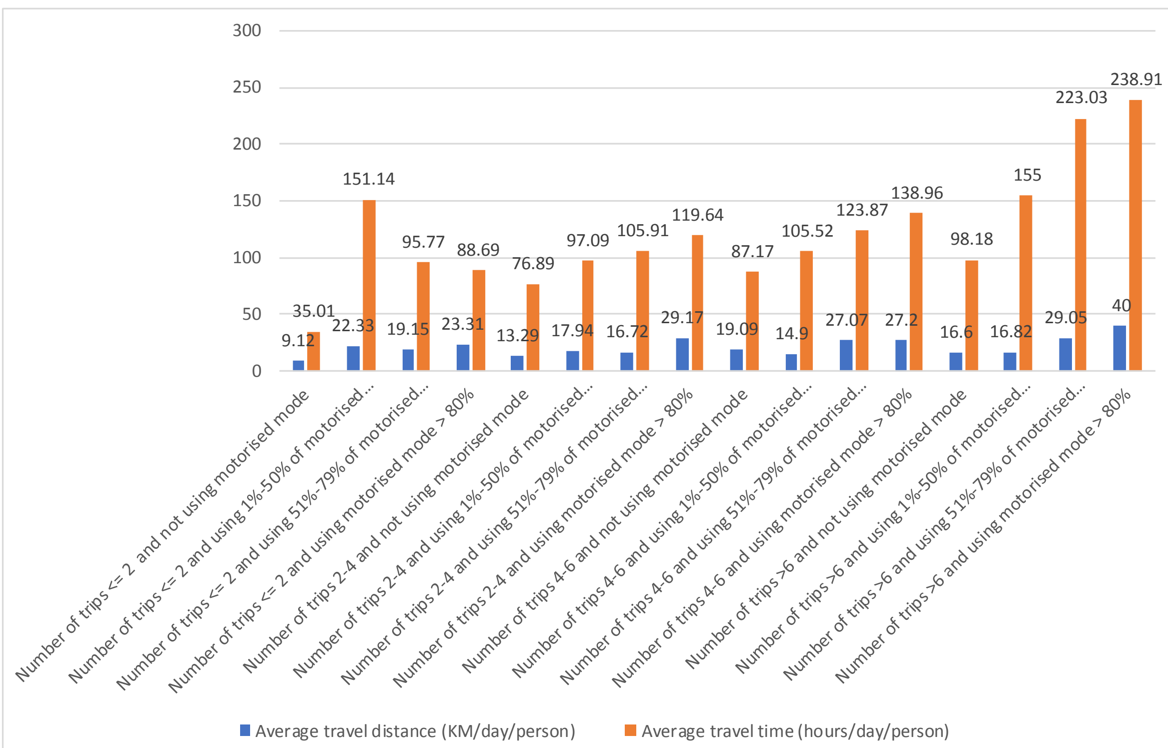


Figure 9. The variability of the average travel distance (Km) and travel time (minutes) per individual by various combinations of number of trips and percentage of motorized use

Table 2. Relationship of residing on the different sides of BMA with density measurements, perceived accessibility, and trip parameters

Area	Population Density	The percentage of the settlement area	The percentage of trade/shopping center area	The percentage of industrial area	The percentage of government office area	The percentage of agriculture area	Land use diversity
CBD	18,165.05	65.61%	3.59%	0.09%	1.00%	0.77%	0.21
Suburban	13,575.57	58.16%	0.20%	1.50%	0.52%	4.60%	0.18
Greater BMA	4,785.65	23.51%	0.06%	5.01%	2.62%	14.88%	0.31

Area	Perceived travel time to CBD	Perceived travel time to the grocery store	Perceived travel time to park	Perceived travel time to a shopping center	Number of trips	Number of trip chains	Travel time
CBD	18.70	4.98	14.70	11.88	2.47	1.15	68.83
Suburban	29.05	7.66	15.74	15.93	2.59	1.18	76.00
Greater BMA	39.28	10.69	24.55	16.81	2.35	1.07	80.09

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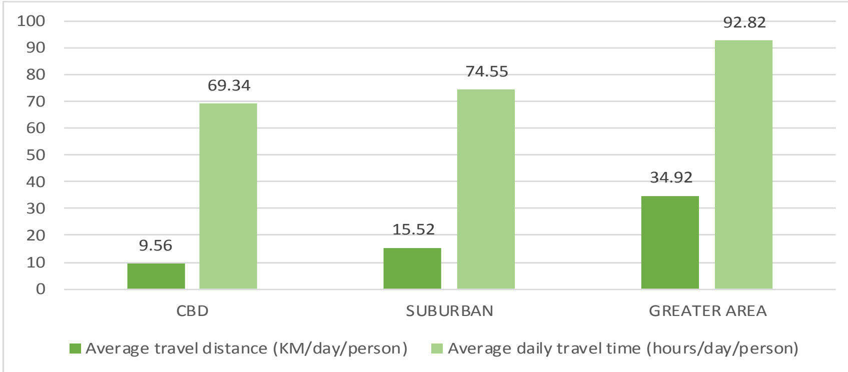
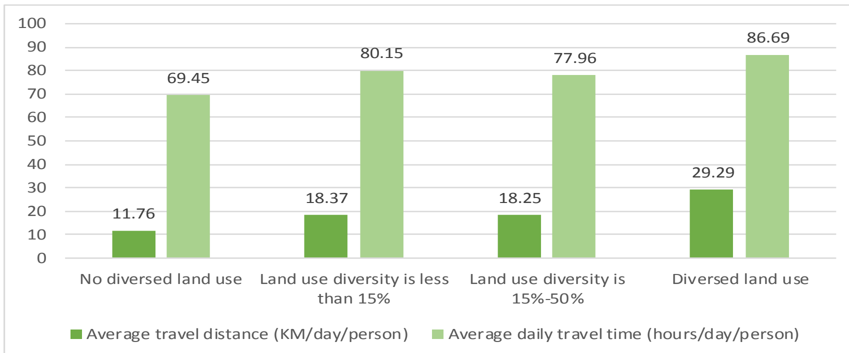
Table 3. Relationship of residing in a particular area with perceived accessibility, and trip parameters

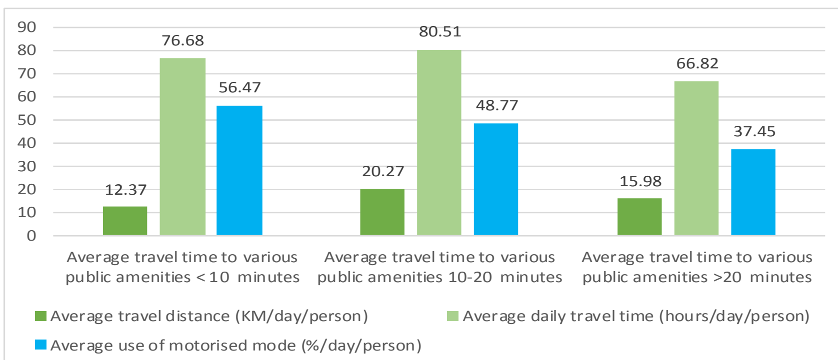
Area	Perceived travel time to CBD	Perceived travel time to the grocery store	Perceived travel time to park	Perceived travel time to the shopping center	Number of trips	Number of trip chains	Travel time
Low population density	36.92	9.77	19.09	17.48	2.33	1.09	78.02
High population density	20.84	5.73	16.89	12.83	2.83	1.24	73.99
The low percentage of trade/shopping center	34.90	8.98	20.59	16.56	2.55	1.16	78.65
The high percentage of trade/shopping center	18.98	6.19	10.74	13.41	2.35	1.09	69.75
Shorter perceived travel time to the city center	13.19	7.20	11.50	12.85	2.65	1.21	73.50
Longer perceived travel time to the city center	45.27	9.22	23.62	18.16	2.39	1.09	79.00
Suburban areas	29.24	7.69	15.61	15.98	2.58	1.17	75.72
Areas in Greater BMA which are closer to the city center	24.71	7.91	26.92	16.66	2.18	0.97	85.78
Areas in Greater BMA which are farther from the city center	46.50	12.08	23.54	17.60	2.35	1.09	75.71



(a) Residential location effect

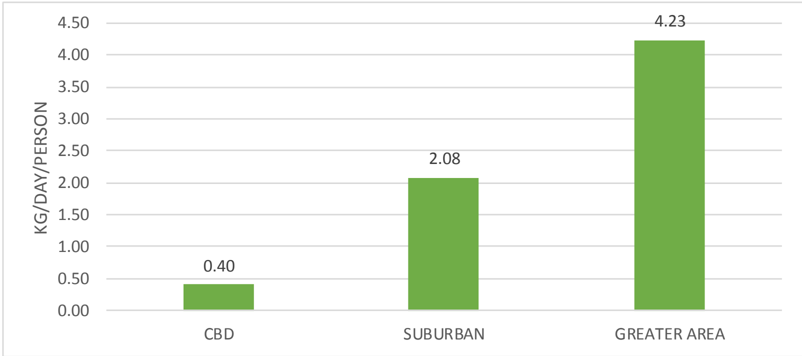


(b) Degree of land use diversity of residential location

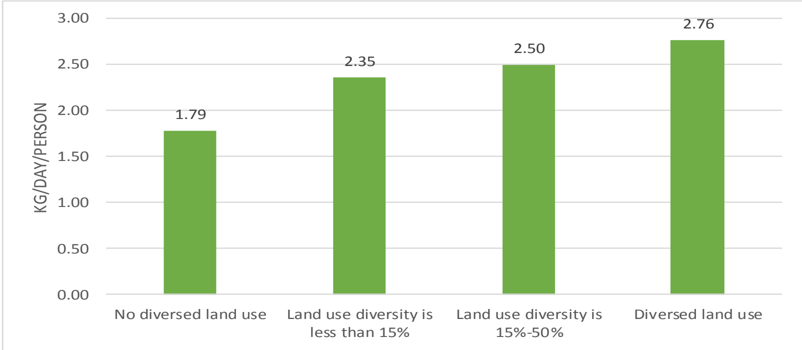


(c) Average travel to various public amenities in residential location

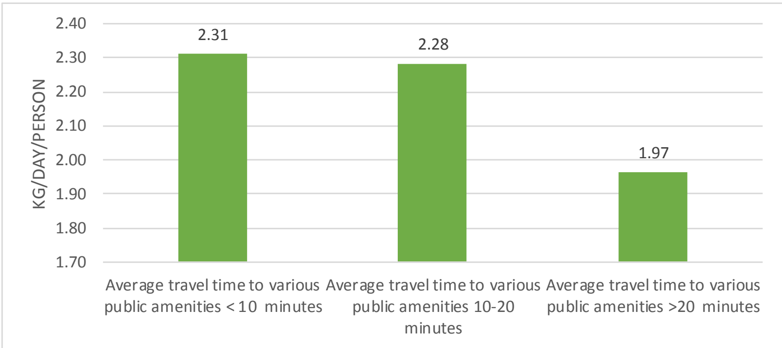
Figure 10. The variability of the average travel distance (Km) and travel time (minutes) per individual by various built environment conditions of respondents' residential locations



(a) Residential location effect



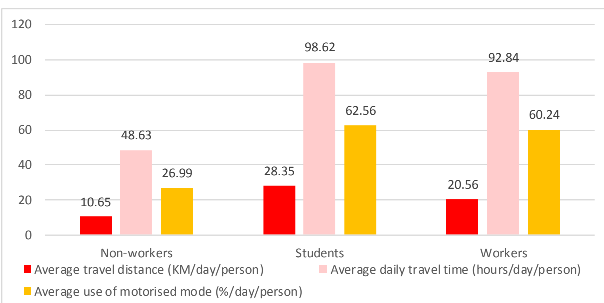
(b) Degree of land use diversity of residential location



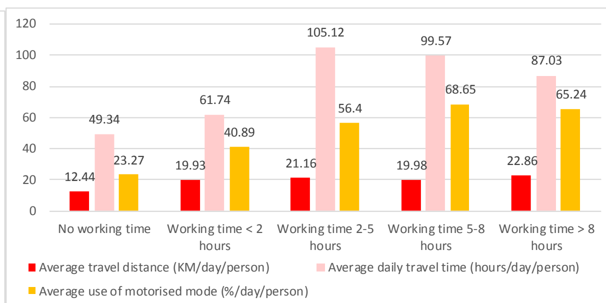
(c) Average travel to various public amenities in residential location

Figure 11. The variability of the average Kg- CO_2 emissions per individual by various built environment conditions of individuals' residential areas

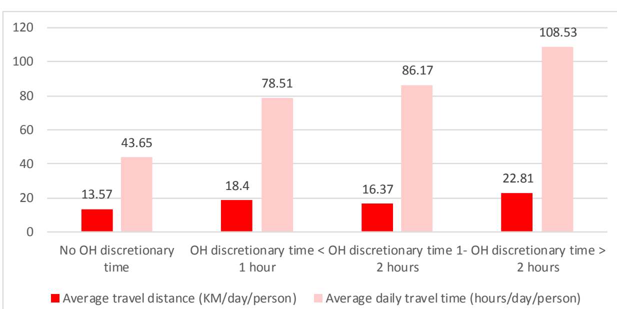
Time flexibility and high exposure to private vehicles of those who work 2-5 hours might correspond with farther and longer travel productions (fig 12) and more number of trips and trip chains (fig 13) than someone with fixed schedules such as workers with longer working commitments (also found in Dharmowijoyo et al., 2014, 2016; Manoj and Verma, 2017), which resulted in higher CO_2 emissions. On the other hand, those who have commitments to work less than 2 hours correspond with the highest number of trips but shorter travel productions which make them emit lower CO_2 than those who have longer working commitments as shown in Figures 12 and 13. The commitments to work above 5 hours correspond with higher dependency on private vehicles as above 65% of their daily use as shown in Figure 12. Commitments to undertake out-of-home discretionary and social-recreation activity shorter than 1 hour may make someone travel farther distance, but with shorter travel time, hence lower CO_2 emissions compared to the counterparts (fig. 12). There might be a trade-off between the duration of the out-of-home discretionary and social-recreation activity, and travel time duration and/or frequency of undertaking out-of-home discretionary trips defined as the friction of distance (Ellegård and Villhemson, 2004; Dharmowijoyo et al., 2018).



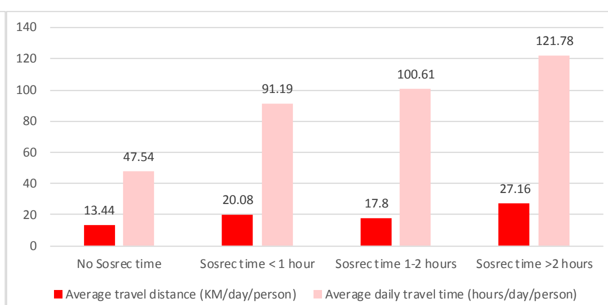
(a) Occupation type



(b) Working time



(c) Out-of-home discretionary time



(d) Social-recreation time

Figure 12. The variability of the average travel distance (Km) and travel time (minutes) per individual by various travel pattern combinations between the number of trips and percentage of motorized use

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The ones who undertake the longest working hour tend to have the least opportunities to negotiate their time to do more out-of-home discretionary and/or social-recreation activity during the day and might have the farthest commuting distance. The ones who undertake 2-5-hour working time might have higher opportunities to negotiate their time to undertake longer out-of-home discretionary and social-recreation activity in farther distances than the ones who work 5-8 hours a day and as might be confirmed in Figure 13. Therefore, linking Figures 12, 13, 14, and 15, having the farthest travel distance confirms how the ones who work 2-5 hours and more than 8 hours a day tend to emit the highest CO_2.

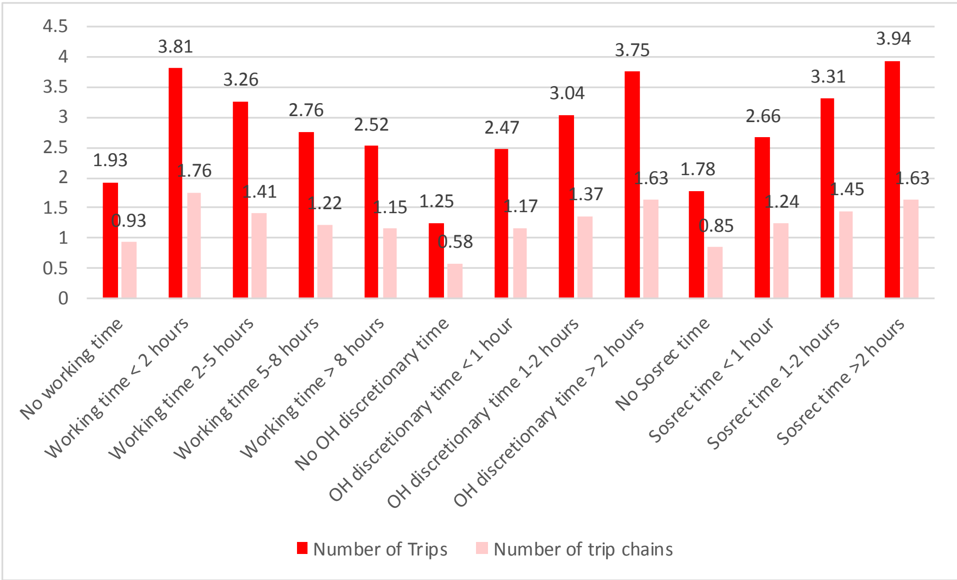


Figure 13. The variability of the number of trips and trip chains per individual by various activity patterns

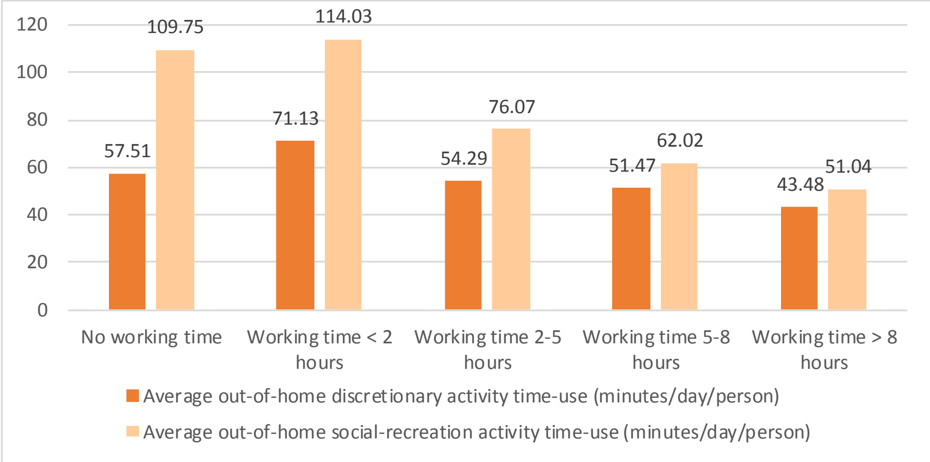
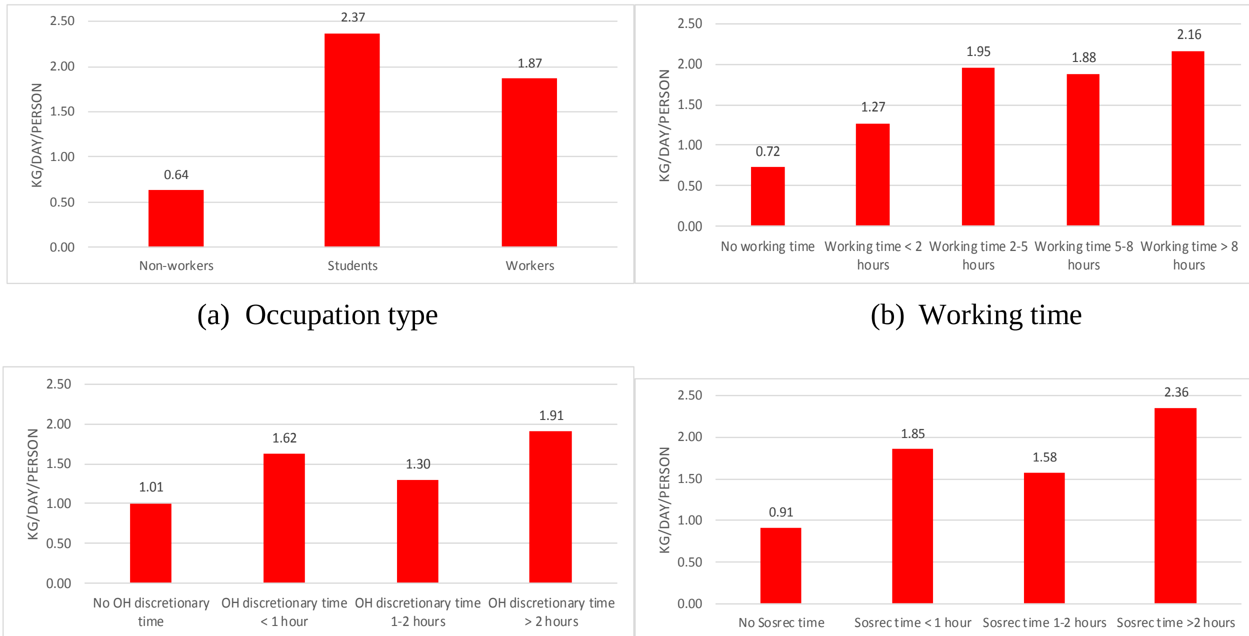


Figure 14. The variability of the average time spent for out-of-home discretionary and social recreation (minutes) per individual by various activity patterns



(a) Occupation type (b) Working time

(c) Out-of-home discretionary time (d) Social-recreation time

Figure 15. The variability of the average Kg- CO_2 emission per individual by various activity pattern

DISCUSSIONS AND CONCLUSION

This study shows that the disaggregated modeling on estimating CO_2 emissions might be able to indicate which individuals can be targeted to reduce their CO_2 emissions and can indicate some policies for reducing CO_2. Those who have commitments to do some trips more than 6 and trip chains of more than 2 might have more dependency to use private vehicles either private cars or motorcycles and travel farther and longer. Those people might be difficult to be persuaded to reduce their motorized mode dependency due to their high commitments to have more trips and visit more locations, which in turn produce high travel productions and emit high CO_2. More trips and trip chains due to more commitments of working and discretionary trips may make those who have 2-5 hour working commitments correspond with higher travel productions than those with working commitments longer than 5 hours which makes them difficult to shift to more sustainable transport.

Female part-timer workers or female non-workers, and senior citizens tend to have the lowest contributions to CO_2. These people should be persuaded to keep reducing their CO_2 by providing acknowledgments. Some limited incentives can be introduced to female part-time workers/non-workers and senior citizens. Those who have daily travel time below 106 minutes as shown in Figure 16 might be able to be targeted to reduce their dependency on private vehicles. These people are likely those who have more options to use other modes and have trips less or equal to 4. Individuals or workers who take only 2 trips can be targeted to shift their trips using non-private vehicles by introducing more incentives. This group also includes travelers who take 2 or 2-4 trips per day with taking private vehicles more than 80%. More incentives for taking more sustainable trips might be able to shift these people to reduce their dependency to use private vehicles.

Those whose travel time is below 125 minutes per day might be the next groups to be targeted to reduce their CO_2. They are those who correspond with trips below 6 per day but use most of their time to take private vehicles. Providing incentives such as internet vouchers or vouchers to use ride-sourcing routinely might help to shift their travel habit by taking some of their trips using the non-motorized mode, public transport, and/or ride-hailing services. Keeping public amenities at a farther distance might reduce people to increase trips and travels using motorized mode. But increasing the distance might make effects social exclusion, in turn, social health (Dharmowijoyo et al., 2020).

Lacking access to improved pedestrian and cycling networks are among the reasons why people who reside in more diverse land use as in CBD, suburban, and some greater areas in the West part of BMA are often opting the private vehicles. Whereas more options of dedicated public transport to greater areas might be able to give alternatives to greater areas residents to shift to more sustainable modes as indicated as well by Dharmowijoyo et al. (2020, 2021b).

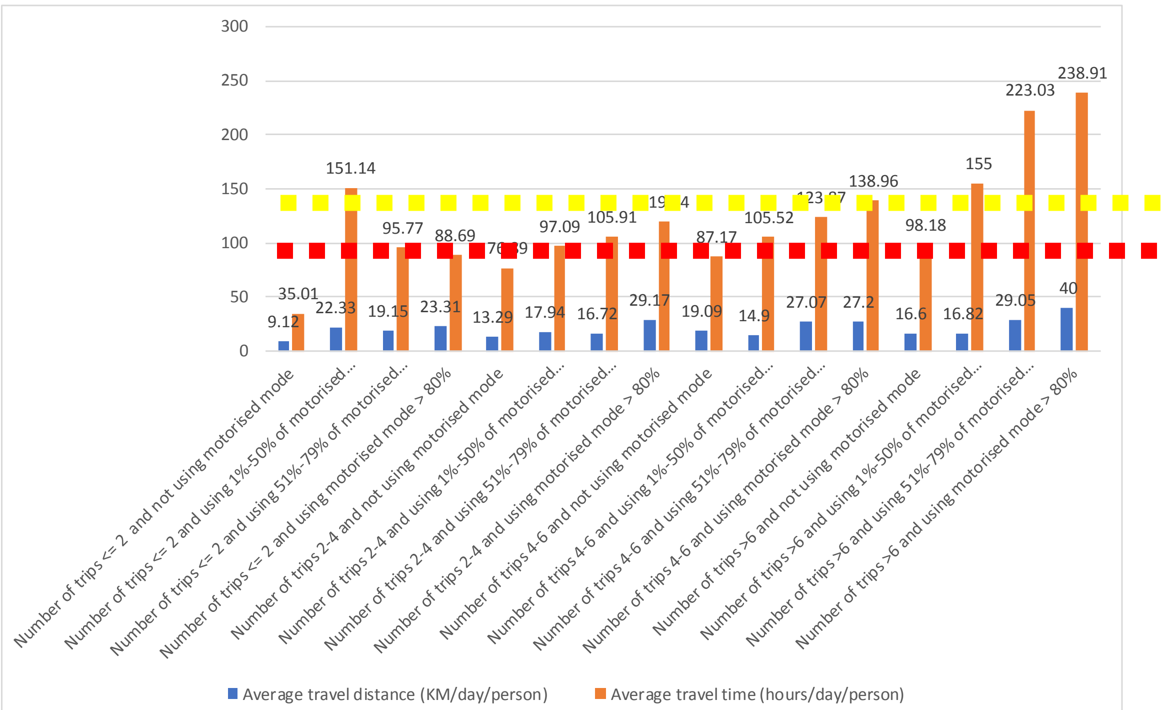


Figure 15. Groups of individuals who have shorter travel time than 106 minutes and lower than 125 minutes

With this study, some insight policies can be indicated considering their activity-travel behavior. Indicated incentives to some indicated persons are also shown. More advanced models are suggested to be done. Moreover, since ride-sourcing modes were not booming in 2013, BMA 2013 dataset did not include ride-sourcing modes. Therefore, data collections including ride-sourcing are expected to provide more insights on whether ride-sourcing can role as an alternative to public transport compared with the conventional public transport system. Some studies in Indonesia indicated that ride-sourcing can shift private motorcycle users to use this mode (Irawan et al., 2019; Rizki et al., 2021). It means that ridesharing using ride-sourcing modes might be able to be used to reduce CO2 production.

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