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Exploring the Intrinsic and Extrinsic Motivations Behind Electric Motorcycle Adoption in Yogyakarta, Indonesia

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ABSTRACT The rapid rise in motorcycle usage in Indonesia has contributed significantly to urban transport emissions, underscoring the need for cleaner alternatives such as electric motorcycles (EM). This study investigates the roles of extrinsic motivation (e.g., policy incentives) and intrinsic motivation (e.g., residential location, daily activity patterns, and psychological readiness) in shaping EM adoption in Yogyakarta, Indonesia. A stated preference survey was conducted with 400 conventional motorcycle owners, collecting socio-demographic data, four-day activity diaries, perceived accessibility measures, and responses to a transtheoretical model questionnaire. Using a mixed logit modelling framework, three models were estimated, progressively incorporating vehicle attributes, policy incentives, spatiotemporal factors, travel satisfaction, and behavioural readiness stages. Results show that spatial context, particularly residing farther from the city centre, public transport, and parks, has a stronger effect on EM adoption than readiness stage, with workaholic activity patterns also positively associated. Among policy measures, free battery replacement emerged as more influential than free annual vehicle tax, although range, maintenance cost, and charging time remained more critical determinants. Behavioural readiness moderates these effects: individuals in the preparation stage are significantly more likely to adopt EMs, while those in contemplation are less inclined. The findings suggest that beyond financial incentives, campaigns emphasizing EM reliability and environmental benefits, targeted toward suburban residents and high-usage riders, could accelerate adoption. These insights support spatially and behaviourally segmented strategies for promoting low-emission transport in motorcycle-dependent, rapidly motorizing cities, and inform the potential integration of market-based mechanisms such as personal carbon trading or tradable driving credits.

KEYWORDS activity-travel patterns; electric motorcycle; residential location; transtheoretical model; travel satisfaction

1 INTRODUCTION

From 1990 to 2016, carbon dioxide (CO_2) emissions from the transport sector steadily increased (Our World in Data, 2021). In Indonesia, the road transport sector alone contributed 91% of total CO_2 emissions (Ministry of Energy and Mineral Resources of Indonesia, 2012; Sukarno et al., 2016), with passenger transport accounting for approximately 60%. To address this, strategies such as the use of electric vehicles (EVs), expansion of public transport, and promotion of alternative mobility options like ride-sourcing and cycling have been widely encouraged (Huang and Ge, 2019). EVs include both electric cars (ECs) and electric motorcycles (EMs), the latter of which are especially relevant in the Indonesian context.

Between 2014 and 2018, Indonesia was the third-largest motorcycle producer globally, after India and China, and the largest in Southeast Asia (Firmansyah et al., 2024). In 2018, motorcycles dominated travel in the Jakarta Metropolitan Area (JMA), comprising 75.1% of all trips, compared to just 15.9% by car and 9.03% by public transport (JICA, 2018). This marked a steep increase from previous years, 55.1% in 2010 and 21.4% in 2002, reflecting a broader shift toward private vehicle ownership as income levels rise (Inklaar, 2018). Given this trend, transitioning from conventional motorcycles (CMs) to EMs is essential to reducing emissions, making it crucial to understand the factors driving EM adoption in a motorcycle-dependent country like Indonesia.

Previous EM studies conducted in Taiwan (Chiu and Tzeng, 1999; Huang, 2024), Vietnam (Nguyen et al., 2024; Su et al., 2023), and Indonesia (Guerra, 2019; Murtiningrum et al., 2022; Rizki et al., 2024; Waluyo et al., 2022) have largely concentrated on technical attributes and socio-demographic influences. However, the combined influence of extrinsic motivation (e.g., financial incentives) and intrinsic motivation (e.g., lifestyle, travel behaviour, residential context, and psychological readiness) remains insufficiently explored. Additionally, while the Transtheoretical Model (TTM) has been widely applied to behavioural change research, its application to EM adoption is still limited. This study addresses these gaps by integrating EM attributes, policy incentives, and various behavioural and spatial factors, such as residential location, activity-travel patterns, travel satisfaction, and readiness to adopt, into a unified modelling framework. Using a stated preference survey and a mixed logit model, the study analyzes how these interrelated variables influence EM adoption decisions in the Yogyakarta Metropolitan Area (YMA), which covers Yogyakarta city, six districts in Sleman Regency (Depok, Ngaglik, Mlati, Godean, Gamping, and Ngemplak), and three districts in Bantul Regency (Kasihan, Sewon, and Banguntapan). Data were collected from 400 CM owners in the region, including four-day activity diaries and stated preference responses related to EM adoption. By incorporating behavioural staging and latent situational factors, the study offers a deeper understanding of how motivation and context shape the adoption of low-emission transport in motorcycle-dependent urban environments.

2 LITERATURE REVIEW

Government interventions play a vital role in promoting low-emission transport technologies (Huang et al., 2018; Li et al., 2020), but the willingness and ability of individuals to adopt such technologies remain essential (Peattie, 2010). Incentives like tax exemptions and reduced operating costs have proven effective in encouraging EV adoption in various contexts (Yuniaristanto et al., 2024; Langbroek et al., 2016). In EM studies, commonly analyzed attributes include purchase price, speed, range, operating and maintenance costs, and charging duration (Chiu and Tzeng, 1999; Jones et al., 2013; Guerra, 2019). Socio-demographic factors such as age and income also influence adoption decisions (Chiu and Tzeng, 1999; Jones et al., 2013; Guerra, 2019).

Some incentives effective in EC adoption, such as free parking or bus lane access (Arifianto et al., 2024; Hackbarth and Madlener, 2016; Li et al., 2020), are less applicable in Indonesia, where motorcycle parking is already inexpensive and dedicated lanes are scarce. Given that purchase subsidies are already available, operational cost incentives may be more influential. Free battery replacements and vehicle tax exemptions could also support emerging market-based instruments such as personal carbon trading (PCT) and tradable driving credits (TDC), as seen in China (Li et al., 2020), and other developed countries (Dogterom et al., 2018).

Spatial and situational factors also shape transport behaviour. Residential location affects accessibility, travel needs, and ultimately, mode choice (Næss, 2015; De Vos et al., 2021). While in many developed countries, city centre residents rely less on private vehicles due to compact land use and public transport access, the opposite trend is observed in Indonesia, where road-oriented development in urban centres promotes motorcycle use (Dharmowijoyo et al., 2016). Travel distance and accessibility to amenities further influence choices, as shown in both developed and developing contexts (de Abreu e Silva et al., 2012; Dharmowijoyo et al., 2017; Næss et al., 2019).

Geographic patterns are often associated with daily travel commitments and activity-travel patterns, which may also affect EM suitability (Zhao and Zhang, 2018; Scheiner, 2016). Individuals with higher activity engagement or long daily travel distances may find EMs less practical due to range concerns. This aligns with the hierarchical decision structure in travel behaviour, where long-term decisions like residence location interact with short-term travel needs (Van Acker et al., 2010). In addition, travel satisfaction can influence openness to change; satisfied users may be less inclined to shift to new modes, including EMs (Abou-Zeid and Ben-Akiva, 2012; Abenoza et al., 2017; Rizki et al., 2021).

Behavioural and psychological factors are also key to understanding EM adoption. Even within similar demographic groups, differences in habits, values, and readiness to change lead to varied behaviours (Moons and de Pelsmacker, 2012; Schuitema et al., 2013; Langbroek et al., 2016; Chu et al., 2019). While the theory of planned behaviour has often guided EV research, only limited studies have applied non-instrumental variables in EM choice models. This study draws on the TTM, which categorizes behavioural readiness into precontemplation, contemplation, and preparation stages.

Unlike studies in developed contexts, where environmental awareness is often high, applying TTM in a developing context like Indonesia offers insight into whether people are simply aware of EMs or actively preparing to adopt them. Understanding these behavioural stages can help determine whether direct incentives or awareness campaigns are more effective in encouraging EM adoption. TTM also provides a framework to assess whether users have been sufficiently convinced of EMs' reliability and environmental benefits.

3 DATA DESCRIPTION

The survey was conducted between 8 October 2019 and 20 January 2020 and involved 400 motorcycle owners from the YMA. Respondents were selected using the

Table 1. Attributes and their levels

	Conventional motorcycles (CM)	Electric motorcycles (EM)
Purchasing price (IDR millions)	12, 15, 19	17 (subsidised price), 23, 26
Maximum range (km)	110, 150, 200	40, 75, 110, 150
Charging battery time (hours)	0	1, 2, 3, 4
Maximum speed (km)	75, 125, 140	35, 50, 75, 100
Maintenance cost/month (IDR thousands)	75, 100, 150, 200, 250	0, 50, 150
Free annual vehicle tax	No	Yes and No
Free battery exchange	No	Yes and No

probability proportional to size method, in which the probability of selection was based on the population size of each district (i.e., *kecamatan*). Population data were used to define strata where districts with larger populations contributed more respondents, ensuring spatial representativeness across the YMA. Within each selected district, respondents were chosen randomly to avoid selection bias. Of the 400 respondents, 155 also had access to private cars. On average, each respondent owned 2.41 private vehicles, and 68.2% reported owning more than one.

There were three stages to the survey. The first stage comprised the stated choice experiment and TTM survey, which surveyors also used to start building personal interactions with the potential respondents. Moreover, in the first stage, surveyors requested the availability of respondents to take part in the other two stages. Respondents were also informed about the incentives that they would receive by the end of the survey period. The incentives were assumed to be more than figurative but less than a real payment (Huff and Hanson, 1986; Dharmowijoyo et al., 2016). With the inclusion of the activity diary survey, 0.031% of the YMA was sampled, which is higher than that achieved using similar efforts in the Bandung Metropolitan Area in 2013 (Dharmowijoyo et al., 2016).

The attributes of CM and EM used in the stated choice experiment survey are shown in Table 1. A D-efficient design by Ngene (ChoiceMetrics, 2014) was used to determine the experimental design. There were four blocks, and each respondent received a block with six choice experiments. Each choice experiment had different values of attributes. In total, there were 2400 observations from 400 respondents. In addition, the TTM contained four questions belonging to the pre-contemplation stage, three to the contemplation stage, and two to the preparation stage. Because EM still has low penetration in Indonesia and the YMA as well, action and maintenance questions were not asked. Therefore, in the survey, the authors and survey team approached respondents who had not yet owned an EM. All questions related to each stage had been chosen carefully from published studies (Prochaska and Velicer, 1997; Friman et al., 2017).

In the second stage, socio-demographic information was collected, including gender, age, income, household numbers, and some residential location questions

Table 2. Activity classifications

Activities used in the research	Activity classifications in the survey
IH mandatory	Sleeping, personal activities, eating at home
IH and OH working and studying	Working and studying either at home or out-of-home
Pick up/drop off	Pick-up and drop-off of children and other household members
IH and OH leisure	Watching TV/listening to radio/music without internet connections, reading newspapers/magazines/comics, relaxing or daydreaming at home and out-of-home OH leisure also includes going to the cinema/park/playground, going to recreation and sightseeing shopping
IH and OH socializing	Talking/texting with household members/relatives/colleagues/friends either using phone/internet connections or not, visiting/receiving friends/relatives, meeting with friends/relatives, including religious gathering and volunteering/politics activities at home or out-of-home
IH maintenance	Household activities and in-home babysitting
Grocery shopping	Going to the grocery store
Other maintenance	Going to bank/post office/health centre, out-of-home babysitting
Sport activities	Doing sports activities at out-of-home. Sports are not found at home
IH and OH online activities	Social media activities, playing the game online, watching movies from internet platforms, browsing, reading online news, and any related online activities related to leisure

IH means in-home, OH means out-of-home

Table 3. Profile of all respondents (400 individuals)

Variables	Percentage or Mean
Socio-demographic characteristics at the individual level:	
Male	53.80%[1]
Workers and non-workers	79.2%[1]
Young adult (Aged 15–22 years old)	11.80%[1]
Aged 23–45 and 45–55 years old	69.50% and 12.80%[1]
Part of low-income (< IDR 3 million/month) and medium-income households (IDR 3–6 million/month)	43.30% and 40.00%[1]
Household characteristics:	
Number of private vehicles per household	2.17
Having access to a private car and private vehicles (including private CM)	38.8% and 98%
Activity-travel patterns on weekdays (and on weekends)	
Percentage of travel time using private transport on weekdays (on weekends)	36.78% (31.49%)
Percentage of travel time using private conventional motorcycles on weekdays (on weekends)	62.43% (50.03%)
Percentage of travel time using private cars on weekdays (on weekends)	26.98% (26.39%)
Percentage of travel time using public transport (on weekends)	4.59% (8.57%)
Percentage of travel time using non-motorised mode (on weekends)	9.77% (13.59%)
Percentage of travel time using ride-sourcing mode (on weekends)	0.12% (0.43%)
Total travel time spent in minutes on weekdays (on weekends)	100.54 (98.04)
Time spent on in-home mandatory activities in minutes on weekdays (on weekends)	569.84 (602.53)
Time spent on in-home leisure activities in minutes on weekdays (on weekends)	163.61 (222.43)
Time spent on in-home maintenance activities in minutes on weekdays (on weekends)	88.95 (115.41)
Time spent on in-home online activities in minutes on weekdays (on weekends)	46.89 (57.32)
Time spent on in-home working/school activities in minutes on weekdays (on weekends)	48.33 (35.88)
Time spent on out-of-home working/school activities in minutes on weekdays (on weekends)	289.95 (112.59)
Time spent on pick-up and drop-off in minutes on weekdays (on weekends)	3.47 (3.37)
Time spent on grocery shopping in minutes on weekdays (on weekends)	8.72 (12.94)
Time spent on out-of-home other maintenance in minutes on weekdays (on weekends)	29.84 (27.04)
Time spent on out-of-home socializing in minutes on weekdays (on weekends)	47.57 (95.39)
Time spent on out-of-home leisure in minutes on weekdays (on weekends)	9.60 (7.26)
Time spent on out-of-home sport in minutes on weekdays (on weekends)	5.21 (13.54)
Time spent on out-of-home online activities in minutes on weekdays (on weekends)	5.81 (3.23)
Perceived accessibility variables	
Perceived travel time to the city centre and government office area (minutes)	26.31 and 17.89
Perceived travel time to bank/post office and schools (minutes)	7.67 and 6.36
Perceived travel time to hospital and health centre (minutes)	11.47
Perceived travel time to public transport nodes (minutes)	19.34
Perceived travel time to grocery stores (minutes)	8.25
Perceived travel time to shopping centre (minutes)	18.77
Perceived travel time to park (minutes)	17.91
Transtheoretical Model (TTM)	
I recall information people had given me on whether I will take EM (Pre-contemplation/PC question)	4.70
I react emotionally to the information regarding the new mode as EM (PC question)	4.11
I consider the view that EM can help the environment or reduce CO_2 emissions in an area (PC question)	5.49
I find society changing in ways that make it easier for the users of EM (PC question)	4.93
My dependency on CM makes me feel disappointed (Contemplation/C question)	4.44
I do not use EM now, but I can try to improve my basic level of knowledge to use and to do maintenance of EM (C question)	4.51
I do not use EM now, but I can learn how to use and do maintenance on EM (C question)	4.67
I make commitments to use EM (Preparation/P question)	4.50
I prepare myself to gradually change to use EM (P question)	4.39
I am completely satisfied with my last week's daily travel	5.11
My travel facilitated my last week's daily life	5.19
When I think of my last week's daily travel, the positive aspects outweigh the negative	5.21
I do not want to change anything regarding my last week's daily travel	4.45
My last week's daily travel makes me feel good	4.92

[1] *means that the remaining are females (48.90%), students (27.60%), senior citizens (7.1%), part of high-income households (12.20%), and reside within the CBD (24.50%)*

regarding the perceived accessibility to various public amenities (e.g., perceived travel time to city centre (i.e., central area of Yogyakarta City), bank and post office, grocery stores, and public transport nodes). Perceived accessibility was measured by using an individual's perceived travel time to various public amenities and the city centre. The perceived travel time was assumed to be measured using private vehicles as the dominant transport mode in the YMA. As discussed in section 2, travel distance is still a major problem in the cities of developing countries, such as the YMA. Residing farther from the city centre corresponds to longer daily travel times and longer perceived travel times to various public amenities. Therefore, perceived travel time as a proxy of travel distance is considered to be a better variable for classifying the residential location situation (RLS) across the study area. In addition, this stage asked the individuals to rate their daily travel satisfaction (TS) based on five questions related to cognitive travel well-being derived from Diener et al. (1985). The respondents were asked to answer each question with a 7-point Likert scale ranging from 1 (disagree) to 7 (agree).

In the third stage, activity diaries were collected. The aim was to show the time-use characteristics of respondents, which were hypothesised to correlate with EM adaptation. The activity diary included four consecutive days from Saturday to Tuesday, or two weekend days and two weekdays between the survey timeframes. Twenty-five activity classifications were used, then categorised into mandatory, leisure, maintenance, and online activities. The activity classifications also categorised whether the activities were performed in-home or out-of-home. The travel mode classification also included the on-demand transportation and ride-sourcing modes. The detailed activity classifications are shown in Table 2. Table 3 shows the sample profiles with all socio-demographic variables, built environment conditions, and activity-travel patterns, including the questions of the TTM and TS and their profiles.

4 MODEL ESTIMATION

4.1 Mixed logit model

EM adoption was modelled by using a mixed logit model in the random utility theory. Mixed logit models provide three benefits compared with standard logit models: (1) they allow random taste variations, (2) they facilitate correlations of choice heterogeneity, and (3) they represent general substitution patterns (Train, 2009). Each individual (n) answered $t = 6$ choice questions; each choice set contained two-mode alternatives: CM and EM. The utility of respondent n from alternative j in choice question t is described in Equation (1). Explanatory variables (X_{njt}) also included alternative-specific constants, vehicle attributes, RLS, activity-travel patterns, TS, and an individual's stage in EM adoption.

$$U_{njt} = \alpha X_{njt} + \mu_n Z_{njt} + \varepsilon_{njt} \tag{1}$$

where:

X_{njt} and Z_{njt}	explanatory variables of individual n for alternative j and choice question t
α	vector of fixed coefficients
μ_n	vector of random coefficients with mean zero
ε_{njt}	unexplained error terms.

The coefficient α is assumed to be random (not a point estimate) and to follow a distribution specified by the researcher (Train, 2009). Considering this, the respondent n chooses alternative j in a choice set t if and only if alternative j provides a higher utility than other alternatives $(j + 1)$ determined by the systemic part of the utility of alternative j compared with the systemic part of the utility of another alternative $(j + 1)$; this can be expressed as $U_{njt} > U_{n(j+1)t},\ \forall j \neq j + 1.$. However, because some of the coefficients are random, L_{ni} was integrated over all possible values of α, as shown in Equation (2). Equation (3) shows how α', as a random value, estimates all possible values of α'.

$$L_{nj}(\alpha_n) = \frac{e^{\alpha x_{nj}}}{\sum_{j \in J} e^{\alpha x_{n(j+1)}}} \tag{2}$$

$$P_{njt} = \int L_{nj} \cdot f(\alpha')\, d\alpha' \tag{3}$$

The use of the random utility model (RUM) as the foundation of the discrete choice model (McFadden, 1984) has been criticised for its exclusion of behavioural processes in estimating the utility of each alternative (McFadden, 1999). The hybrid choice model (HCM) has been proposed to include behavioural processes or some psychological factors that combine the choice model (based on random utility) with a latent variable model (Walker and Ben-Akiva, 2002). Langbroek et al. (2016) argued that the inclusion of various latent variables could reveal the differences in perceptions of the same package of policy incentives on EV adoption models.

By utilising the HCM, this study included latent variables in the choice model. In addition to psychological factors (e.g., the TTM and TS), spatiotemporal variables represented by RLS and activity patterns were included as other latent variables. The perceived accessibility to the city centre and various public amenities were assumed to be highly correlated with each other, as well as with the various activity durations. Subsequently, the dimension should be decreased to reduce a large number of variables into a smaller set of variables while including more composite information on highly correlated observed variables. Endogenous RLS is expected to contain information on how close/far people's residential locations are to the city centre and various public amenities. RLS might be closer to the city centre but farther from some public amenities or

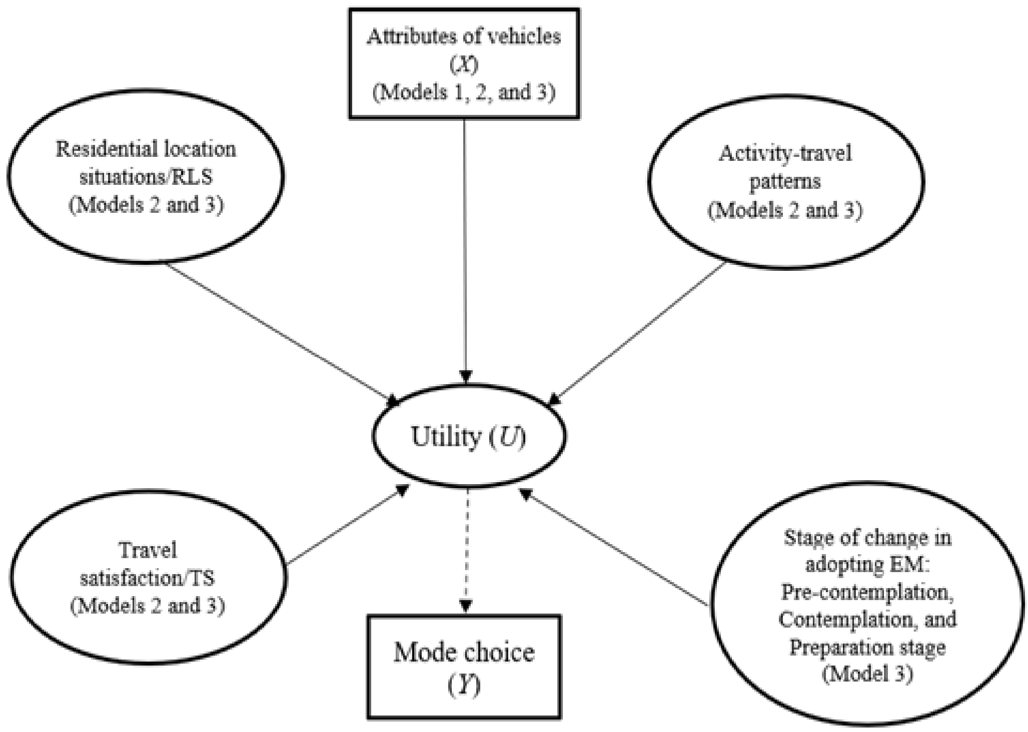


Figure 1 Hypothesized models.

vice versa. However, endogenous activity pattern variables are assumed to show a different set of out-of-home and in-home activity patterns. Those who have longer and shorter working times might have different activity patterns, which may be categorised into two different groups with distinct out-of-home activity patterns. Exploratory factor analysis (EFA) with varimax rotation was applied to identify latent variables of RLS and activity patterns. Varimax rotation is commonly used when there is only one factor expected from the interaction of the multidimensional information of the latent variables (DiStefano et al., 2009). On the other hand, confirmatory factor analysis (CFA) was used to reduce the dimensions of the TTM and TS.

Three models were prepared. Model 1 only contains vehicle attributes and policy incentives for EM adoption. Model 2 includes all situation variables: activity-travel patterns, RLS, and TS in conjunction with vehicle attributes and policy incentives on EM adoption. Model 3 is the same as Model 2, but with the stage of change in EM adoption added. The proposed models are illustrated in Figure 1.

To reduce the computational time of the advanced statistical model, the latent variables (or factors, as defined by Hair et al., 2014) represented by the endogenous factors RLS, activity patterns, TS, and the TTM were not run simultaneously with or were run separately from the mixed logit model. To run the latent variables in the mixed logit model separately, factor scores were estimated to define the factors of the endogenous variables as part of subsequent EFA or CFA (Hair et al., 2014). The factor score is a composite value determined by the interaction of the weight factor and the original values of multiple observed variables that have a mean of zero; the value ranges from −3 to 3 across the samples (Hair et al., 2014). Factor scores were chosen rather than summed ('average' or 'mean' values) because factor scores do not treat the observed variables with the same weight as the latent variables. Equation (4) shows how to find the factor score value left ($\hat{F}_l$) as a product of the factor loading matrix (Λ') of CFA, the inverse of the covariance matrix (Σ^{-1}), and the observed variables (y_i).

$$\hat{F}_l = \Lambda' \Sigma^{-1} y_i \tag{4}$$

4.2 Dimension reduction of residential location and activity pattern variables

There are three RLS categories: areas near the city centre but farther from certain public amenities (grocery stores, shopping centres, and hospitals); areas farther from city centres and various public amenities but near hospitals; and areas located between the first and second areas but farther from banks, post offices, and schools (Table 4).

There are two categories of in-home activity patterns and three categories of out-of-home activity patterns (Table 5). Out-of-home activity patterns include *workers*, *housewives*, and *sports* and *socializing lovers*. *Work-*

Table 4. Factor analysis of built environment attributes

Variables	Component		
	Residing in areas farther from the city centres and public amenities	Residing in areas near the city centre, but farther from grocery stores, hospitals, and government offices	Residing in areas farther from banks, posts, schools, and parks
Perceived travel time to the city centre	0.803	−0.014	0.200
Perceived travel time to public transport nodes	0.854	-	-
Perceived travel time to park	0.620	-	0.382
Perceived travel time to the shopping centre	0.598	0.510	-
Perceived travel time to the government office area	-	0.603	-
Perceived travel time to hospital	−0.199	0.739	-
Perceived travel time to supermarkets	-	0.725	-
Perceived travel time to the bank and the post office	-	-	0.868
Perceived travel time to various schools	-	-	0.800
Extraction Method: Principal Component Analysis; Rotation Method: Varimax with Kaiser Normalisation			
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.792	
Bartlett's Test of Sphericity [χ^2; df; p-value]		[30681.42; 36; 0.000]	
Loadings lower than 0.5 were suppressed (Hair et al.,2014)			

ers contain the out-of-home activity patterns of workers, such as spending more time on out-of-home working, out-of-home maintenance, and out-of-home online activities, whereas *housewives* represent the out-of-home activity patterns of housewives, such as picking up/dropping off children and other household members, spending more time on grocery shopping, and less time on out-of-home leisure. *Sports* and *socializing lovers* seem to allocate more time to out-of-home socializing and sports, and less time to working. In-home activity patterns include in-home online lovers and workaholics. In-home activity lovers likely allocate more time to in-home online activities than offline leisure ones, whereas workaholics seem to spend extra working/studying time at home, which reduces their obligations to perform some core household activities.

As suggested by Hair et al. (2014), each variable with a factor loading < 0.5 was removed. The Kaiser–Meyer–Olkin (KMO) sampling adequacy test was used to measure how suitable the data were for factor analysis. The test value was 0.5, indicating that the data were acceptable for factor analysis (Hair et al., 2014). This study tried to create activity-travel patterns by joining in-home and out-of-home activity patterns, but the KMO adequacy test was less than 0.5. Consequently, separate out-of-home and in-home activity pattern characteristics were applied to create better fit components. Different activity-travel patterns on different weekdays and between weekdays and weekend days might make it difficult to identify in-home and out-of-home activity patterns.

4.3 TS and TTM variables

As shown in Table 6, all variables have a loading factor ranging from 0.5 to 0.929, and higher than the minimum loading factor of 0.5 (Hair et al., 2014). It means that all variables can be accepted to find the factor score. Meanwhile, the values in the parentheses represent the estimated factor score, which shows the mean, minimum, and maximum value of each latent variable. Positive values mean a high level in pre-contemplation, contemplation, preparation stage, and TS. In contrast, negative values mean a low level in pre-contemplation (PC), contemplation (C), preparation (P), and travel satisfaction (TS). From Table 6, it can be seen that each latent variable tended to have different factor scores. Therefore, summed scales or average values were not useful, particularly for contemplation and TS.

5 MXL ESTIMATION RESULTS

Table 7 displays the estimation results. X-standardised coefficients are shown along with unstandardised coefficients for comparing the independent (X) variables with different metrics (Williams, 2022). X-standardised coefficients were chosen because the Y variable (the choice variables) cannot estimate standard deviation for performing full standardised coefficients (Williams, 2022). When comparing the models, Model 2 has a lower Akaike information criterion (AIC) and Bayesian information criterion (BIC) than Model 1 and a lower BIC than Model 3. In contrast, Model 3 has a lower AIC than Model 1. A lower AIC and BIC indicate that less information is lost, indicating that the model is

Table 5. Factor analysis of activity-travel patterns

Variables	Component				
	In-home online activity lovers	Workaholics	Housewives' affairs	Sports and socializing lovers	Workers' affairs
Time spent on in-home mandatory	0.668	-	-	-	-
Time spent on in-home leisure	−0.685	-	-	-	-
Time spent on in-home online	0.553	-	-	-	-
Time spent on in-home maintenance	-	−0.543	-	-	-
Time spent on in-home working and studying	-	0.755	-	-	-
Time spent on out-of-home leisure	-	-	−0.565	-	-
Time spent on out-of-home grocery shopping	-	-	0.581	-	-
Time spent on out-of-home pick up of children and other household members	-	-	0.571	-	-
Time spent on out-of-home working and studying	-	-	-	−0.568	0.307
Time spent on out-of-home socializing	-	-	-	0.560	-
Time spent on sports	-	-	-	0.735	-
Time spent on out-of-home other maintenance	-	-	-	-	0.701
Time spent on out-of-home online	-	-	-	-	0.408
Extraction Method: Principal Component Analysis; *Rotation Method*: Varimax with Kaiser Normalisation					
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.599		0.521	
Bartlett's Test of Sphericity [χ^2; df; p-value]		[915.50; 10; 0.000]		[1651.87; 28; 0.000]	
Loadings lower than 0.5 were suppressed (Hair et al.,2014)					

Table 6. Loading factors of each observed variable on the respective latent variables

Observed variables	Loading factors	Factor scores of latent variables
I recall information people had given me on whether I will take EM (Pre-contemplation/PC question)	0.831	Pre-contemplation stage/PC (0, −3.39, 1.89)
I react emotionally to the information regarding the new mode as EM (PC question)	0.753	
I consider the view that EM can help the environment or reduce CO_2 emissions in an area (PC question)	0.751	
I find society changing in ways that make it easier for the users of EM (PC question)	0.500	Contemplation stage/C (0, −2.77, 2.10)
My dependency on CM makes me feel disappointed (Contemplation/C question)	0.872	
I do not use EM now, but I can try to improve my basic level of knowledge to use and to do maintenance of EM (C question)	0.900	
I do not use EM now, but I can learn how to use and do maintenance on EM (C question)	0.837	
I make commitments to use EM (Preparation/P question)	0.929	Preparation stage/P (0, −2.42, 2.10)
I prepare myself to gradually change to use EM (P question)	0.929	
I am completely satisfied with my last week's daily travel	0.889	Travel satisfaction/TS (0, −3.05, 1.77)
My travel facilitated my last week's daily life	0.843	
When I think of my last week's daily travel, the positive aspects outweigh the negative	0.844	
I do not want to change anything regarding my last week's daily travel	0.693	
My last week's daily travel makes me feel good	0.875	

Table 7. Model estimation results

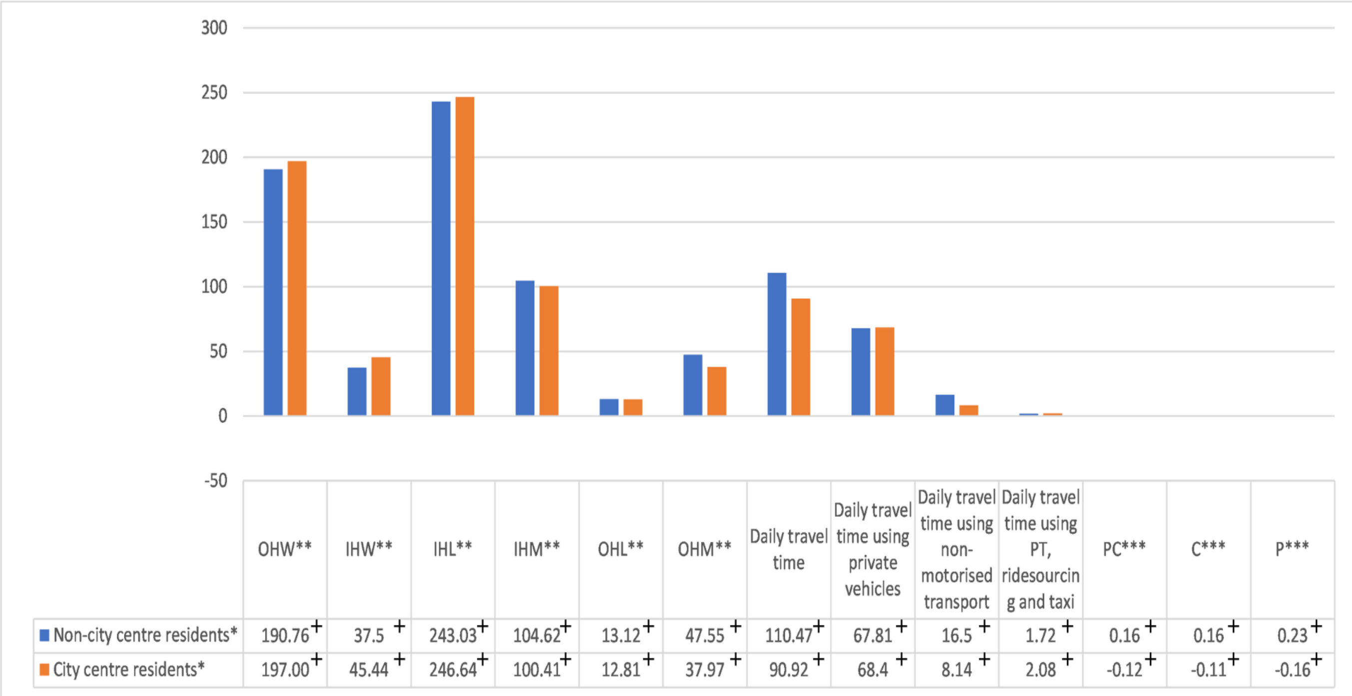
	Model 1 (Only choice variables)		Model 2 (Choice variables, BE and activity-travel patterns)		Model 3 (Choice variables, BE, activity-travel patterns, TTM)	
	Coeff (X-standardised coeff*)	T-stat	Coeff (X-standardised coeff*)	T-stat	Coeff (X-standardised coeff*)	T-stat
The alternative specific constant of EM	**-10.31**	**-3.08**	**-51.59**	**-92.85**	**-47.37**	**-34.21**
Price	**-3.19(−10.99*)**	**-2.2**	**-3.49(−12.02*)**	**301.40**	**-3.48(−11.99*)**	**-301.39**
Maintenance cost	**-18.61(−528.63*)**	**-4.74**	**-0.73(−44.82*)**	**-2.06**	**-0.75(−46.05*)**	**-3.25**
Range	**2.52(89.23*)**	**3.89**	**2.47(87.46*)**	**86.43**	**2.39(84.63*)**	**-133.04**
Charging time	**-10.58(−11.75*)**	**-9.75**	**9.81(10.89*)**	**5.04**	**-5.52(−6.13*)**	**-4.56**
Speed	0.34	-0.64	**0.05(1.37*)**	**8.83**	**0.04(1.10*)**	**2.84**
Free annual vehicle tax	**3.26(1.63*)**	**6.21**	**3.49(1.75*)**	**87.73**	**3.46(1.73*)**	**344.71**
Free battery	**6.36(3.18*)**	**-28.18**	**5.64(2.82*)**	**75.06**	**5.98(2.99*)**	**-157.20**
Standard deviation price	**-3.19**	**6.84**	**-2.89**	**271.67**	**-2.89**	**-271.67**
Standard deviation maintenance cost	**7.21**	**6.25**	**1.21**	**10.16**	**1.25**	**1.92**
Standard deviation range	**7.86**	**6.28**	**-7.03**	**250.16**	**6.92**	**551.19**
Standard deviation charging time	**4.86**	**10.27**	**-3.80**	**0.79**	**2.84**	**9.28**
Standard deviation speed	**-8.92**	**-8.37**	**-8.01**	**-432.87**	**-7.99**	**-972.54**
Standard deviation free annual vehicle tax	**-3.05**	**-6.83**	**-3.71**	**-176.89**	**-3.68**	**-383.80**
Standard deviation free battery	**-12.79**	**56.19**	**-12.79**	**161.99**	**-13.14**	**369.32**
Residing farther from the city centre, public transport networks and parks	-	-	**48.08(48.08*)**	**101.08**	**40.74(40.74*)**	**52.32**
Residing near the city centre but farther from grocery stores, hospitals	-	-	**-14.25(−14.25*)**	**-32.90**	**-27.31(−27.31*)**	**-32.26**
Residing not far from the city centre, but far from bank and post offices	-	-	**-24.63(−24.63*)**	**-40.04**	**-22.97(−22.97*)**	**-35.26**
In-home online activity lovers			0.34	1.23	**0.54(0.54*)**	**2.32**
Workaholics	-	-	**1.07(1.07*)**	**1.87**	**1.46(1.46*)**	**2.87**
Housewives' affairs	-	-	**-0.03(−0.03*)**	**1.86**	0.28	0.49
Socializing and sports lovers	-	-	-0.08	-0.97	-0.17	-0.30
Workers' affairs	-	-	**-0.62(−0.62*)**	**-1.75**	-0.56	-0.84
Travel satisfaction	-	-	**-5.59(−5.59*)**	**-6.48**	-1.04	-1.29
Pre-contemplation stage	-	-	-	-	-0.68	-0.45
Contemplation stage	-	-	-	-	**−0.15 (−0.15*)**	**-3.78**
Preparation stage	-	-	-	-	**4.99(4.99*)**	**3.39**
AIC	3013.19		2915.35		2914.16	
BIC	3120.74		3101.76		3122.08	
Log-likelihood	-1491.596		-1434.49		-1428.08	

Values in bold indicate values with p-value < 0.1, whereas un-bold values are values with p-value > 0.1.
**X-standardised coefficients = un-standardised coefficients of X variable *standard deviation of the respective X variable.*
X-standardised coefficients are used to compare different independent (Xs) variables with different metrics since the binomial mixed logit model does not have a standardised variable of the dependent (Y) variable.

better (Dziak et al., 2019). Moreover, a larger positive likelihood corresponds with a smaller p-value (The Pennsylvania State University, 2018), which means that Models 2 and 3 are better than Model 1. Model 2 is likely better than Model 3. It can be said that, in addition to activity patterns, RLS and TS improve the model specifications.

As expected, increasing purchase price, maintenance costs, and charging time, as well as reducing travel range, significantly reduced the probability of owning an EM in all models. However, increasing the speed of EM significantly increased the probability of purchasing an EM in Models 2 and 3, but not in Model 1. Incentive policies such as free annual taxes and free battery replacements for EM users were significant in all models.

Based on standardised coefficients, travel range and maintenance costs of EM were the main concerns of respondents in the YMA. As expected, purchase price and charging time were no longer their main concerns



	OHW**	IHW**	IHL**	IHM**	OHL**	OHM**	Daily travel time	Daily travel time using private vehicles	Daily travel time using non-motorised transport	Daily travel time using PT, ridesourcing and taxi	PC***	C***	P***
Non-city centre residents*	190.76+	37.5 +	243.03+	104.62+	13.12+	47.55 +	110.47+	67.81 +	16.5 +	1.72 +	0.16 +	0.16+	0.23+
City centre residents*	197.00+	45.44 +	246.64+	100.41+	12.81+	37.97 +	90.92 +	68.4 +	8.14 +	2.08 +	-0.12+	-0.11+	-0.16+

* Non-city centre residents live farther from the city centre, public transport networks, and various public amenities, whereas city centre residents live near the city centre and various public amenities.
** OHW and IHW, out-of-home and in-home working time use, respectively; IHL and IHM, in-home leisure and maintenance time use, respectively; OHL and OHM, out-of-home leisure and maintenance time use, respectively.
*** PC, pre-contemplation; C, contemplation; P, preparation.
\+ Significantly different.

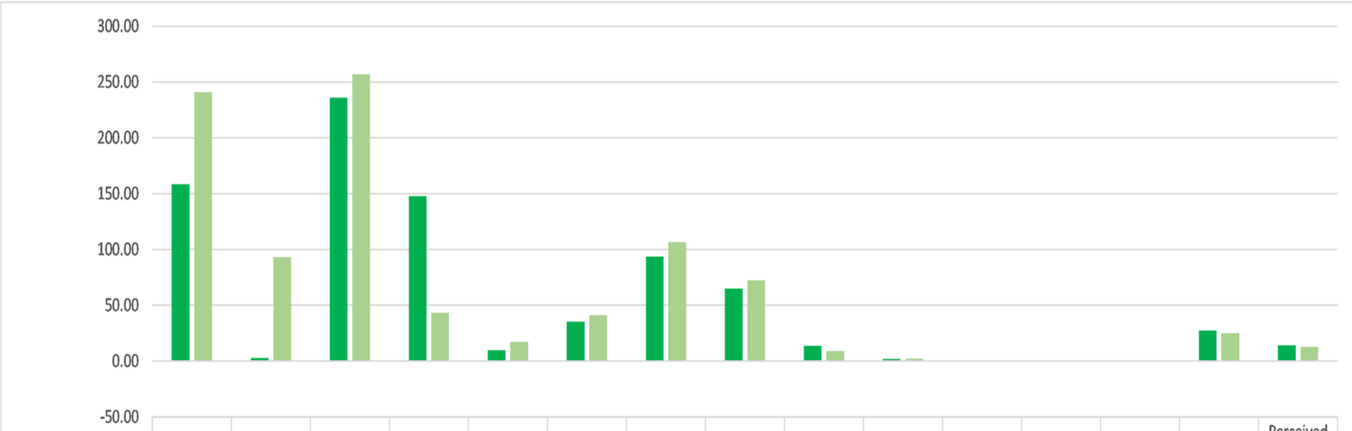
Figure 2 Relationship of residing in a particular area with activity-travel patterns and stage of change to adopt EMs.

because the magnitude effects were weaker than those of range and maintenance costs. Regarding EM performance attributes, speed showed the least influence on EM adoption. Incentive policies seemed to help travellers shift to EM, even though the effect was not as strong as for travel range, maintenance costs, price, and charging time. Overall, free battery replacements appear to be a more promising incentive policy than free annual vehicle taxes; this incentive might help with the EM maintenance costs.

The effects of time-space variables were added in Models 2 and 3. RLS showed greater effects than even purchase price and charging time. The effects were much stronger than the TS and activity patterns in Models 2 and 3. Those who resided farther from the city centre, public transport, and parks correlated positively with EM adoption. Those who resided near the city centre, public transport networks, and parks showed the opposite trends. In Model 2, workaholics correlated positively with EM adoption, whereas workers and housewives correlated negatively with EM adoption. As expected, in Model 2, those who experienced better TS, or better with their current travel situations, including current mode and its coverage range, correlated negatively with EM adoption.

When the stage of change was included in Model 3, TS showed an insignificant impact. In Model 3, the stage of change correlated significantly with EM adoption, with a greater magnitude compared with activity pattern variables. Those who had been at the preparation stage were ready to shift to using EM, whereas those who were still at the contemplation stage tended to do the opposite. For those who were at the pre-contemplation stage, these variables had no impact on the EM model.

Figure 2 shows how RLS corresponds to activity-travel patterns and the stage of change in EM adoption. Offering more exposure to various activity locations between the city centre and suburban areas not only made people who resided farther from the city centre travel significantly longer than travellers who resided near the city centre, but also prompted them to extend their out-of-home discretionary time (a finding consistent with Dharmowijoyo et al.,2020 in developing countries and Scheiner,2016 in developed countries) and provided more opportunities to use non-motorised transport. Areas farther from the city centre were more suitable for walking and cycling. In contrast, areas near the city centre had less space for walking and cycling due to high levels of road-oriented development land use, as reported in previous studies (Dharmowijoyo et al.,



	OHW**	IHW**	IHL**	IHM**	OHL**	OHM**	Daily travel time	Daily travel time using private vehicles	Daily travel time using non-motorised transport	Daily travel time using PT, ridesourcing and taxi	PC***	C***	P***	Perceived average travel time to city centre	Perceived average travel time to various public amenities
Non-workaholics	158.40+	2.79+	236.01+	147.64+	9.69+	35.39+	93.53+	64.89+	13.75+	1.81+	-0.01	-0.01	0.00	27.40+	14.09+
Workaholics	241.07+	93.11+	256.93+	43.21+	17.17+	41.11+	106.41+	72.39+	8.92+	2.1+	0.01	0.02	0.00	24.89+	12.64+

** OHW and IHW, out-of-home and in-home working time use, respectively; IHL and IHM, in-home leisure and maintenance time use, respectively; OHL and OHM, out-of-home leisure and maintenance time use, respectively.
*** PC, pre-contemplation; C, contemplation; P, preparation.
+ Significantly different.

Figure 3 Relationship between in-home workaholics and activity-travel patterns and stage of change to adopt EMs.

2016), but against with results in developed countries (Næss, 2015; De Vos et al., 2021). The opportunity for multimodal behaviours in their daily travel may be a reason why residents of areas farther from the city centre correlate positively with using EM.

Furthermore, as shown in Figure 3, similarly to those who resided farther from the city centre, public transport networks, and parks, workaholics undertook significantly longer out-of-home discretionary time and daily total travel time. Unlike those who resided farther from the city centre, public transport networks, and parks, this group spent significantly longer on working and in-home leisure time, but experienced shorter in-home maintenance time, because they resided closer to the city centre and had a greater dependence on private vehicles in their daily travel than non-workaholics. Although there was no significant difference in the stage of change between workaholics and non-workaholics, workaholics tended to be at a more advanced stage of EM adoption than non-workaholics.

6 DISCUSSIONS AND CONCLUSIONS

This study shows, as in an EC study by Langbroek et al. (2016) that perceiving the same package of EM attributes and policy incentives were also shaped by people's stage of change to adopt EM. This aligns with previous studies in green mobility adoption, where behavioural readiness was shown to be a crucial moderating factor for policy effectiveness (Moons and de Pelsmacker, 2012; Chu et al., 2019). However, basic motivations to adopt EM were not only shaped by having different stages of change, but also by the residential locations and activity patterns of travellers. Specifically, travellers who resided farther from city centres and workaholics correlate positively with EM adoption, which is contrary to findings in Western contexts such as in Sweden and the U.S., where suburban and rural adopters often face greater barriers to EC usage due to low charging infrastructure and longer distances (Westin et al., 2018; Chen et al., 2015).

Travellers who resided farther from the city centre and workaholics have longer daily travel times and out-of-home discretionary activity time, consistent with Scheiner (2016) and Zhao and Zhang (2018), who found that longer daily commitments correlate with the use of efficient, lower-cost transport alternatives. These people might see EM as a way to reduce their daily fuel costs due to their high usage of motorcycles. Campaigns to use EM to people who are not part of these groups might never succeed, highlighting the need to tailor messaging and incentives based on spatial and behavioural segmentation, as also recommended by Schuitema et al. (2013) and Sovacool et al. (2019). It seems that there should be a greater focus on convincing people of the technological and environmental advantages and reliability of EM rather than simply providing incentives or highlighting improved speeds, which resonates with Peattie (2010) and Guerra (2019), who argue that without belief in the reliability or relevance of green technology, incentives alone are insufficient.

However, convincing the technological and environmental advantages of EM should focus on people who reside farther from the city centre, public transport networks and parks; instead of convincing people who reside in other places, particularly near the city centre. This emphasis is supported by Indonesian-specific findings (Dharmowijoyo et al., 2016) showing that city centre residents often rely more on private modes due to poor walkability and lack of dedicated infrastructure for alternative modes.

People still worried about EM performance attributes and costs rather than paid attention to policy incentives, whilst travel range, maintenance costs, purchase prices, and charging time showed greater effects than policy incentives. The range was an important variable because cities in developing countries, particularly in Indonesia, have less compact development due to road-oriented land use developments, which mirrors land-use challenges described in Holz-Rau et al. (2014) and Næss et al. (2019). However, due to living in highly congested areas, speed was not an important EM performance attribute. Free battery replacements would be a better policy than free annual vehicle taxes: this approach could reduce maintenance costs, which have become a bigger concern than the purchase price, as shown in this study.

The significant effects of free annual taxes and free battery replacements on EM adoption models indicated the possibility of implementing PCT and TDC in EM use. This finding complements the arguments in Dogterom et al. (2018) and Li et al. (2020) that market-based mechanisms can promote cleaner transport choices, particularly when operational benefits are clearly framed. EM users could utilise high PCT and TDC surpluses to claim either free battery replacements and/or free annual taxes. On the other hand, PCT and TDC deficits could be used to increase the maintenance costs of CM. Residents who live farther from the city centre and workaholics could see benefits with reduced fuel costs, free annual taxes, and free battery replacements, along with the implementation of PCT and TDC. Dedicated stated choice experiments with detailed PCT and TDC schemes should be conducted to determine whether PCT and TDC are favourable for residents in areas farther from the city centre and workaholics, a direction that mirrors recent experimental transport behaviour studies (e.g., Abenoza et al. (2017); De Vos et al. (2021)).

Although this study offers valuable insights, it also has two main limitations. First, the absence of geographic distribution data for individual respondents across the YMA restricts spatial analysis of adoption behaviour. Future research could benefit from collecting and analyzing respondent location data to capture geographic variation in EM adoption better. Second, the study relies on respondents' perceived travel times, which may introduce subjectivity and individual bias. To improve accuracy, future studies should consider incorporating objective travel time estimates, such as those derived from digital mapping platforms like Google Maps, for comparison with perceived values and to strengthen the analysis of accessibility-related factors.

DISCLAIMER

The authors declare no conflict of interest.

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