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Preferences for electric motorcycle adoption in Bandung, Indonesia

Chandra Balijepalli[a], Simon Shepherd[a], Romain Crastes Dit Sourd[b], Muhammad Farda[c], Tryas Praesha[c] and Harun Al-Rasyid Lubis[c]

[a]Institute for Transport Studies, University of Leeds, Leeds, UK; [b]Leeds University Business School, University of Leeds, Leeds, UK; [c]Institut Teknologi Bandung Jl. Ganesha No 10, Bandung, Indonesia

ABSTRACT
Due to an alarming threat of air pollution and climate change, governments around the world are now actively promoting electric vehicles. The case for vehicle electrification is even more important in big cities of developing countries, where motorcycle is a dominant mode of travel. To promote electric motorcycles successfully, we need to understand the factors that would drive the consumer choices when buying a motorcycle. This study chose Bandung in Indonesia as the case study location, where nearly 75% of vehicles are motorcycles. This study conducted a survey of preferences from over 700 residents and included battery charging methods such as plug-in/battery swap at home/office, superfast charging at stations, and deployed an innovative modelling approach constraining the mixture of distributions for monetary attributes. The study found that quick recharge in 10 minutes and battery swap at station are preferred over the base method of plug-in at home/work. The battery swap at home has been perceived the same as plug-in home/work and the respondents are indifferent to this option.

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KEYWORDS
Electric motorcycles; stated preference; air pollution; climate change

1. Introduction

In response to the growing environmental concerns, federal and local governments worldwide have started identifying potential means to reach the emission reduction targets promoted by the United Nations Sustainable Development (United Nations, 2023). Electric vehicle technology, seen as one of the potential solutions, gained momentum in the last few years. European and North American countries, where car ownership is higher, have focused on introducing electric cars essentially in two different forms – Battery Electric Vehicles and Plug-In Hybrid Vehicles. This is also the case for China with one of the largest Battery Electric Vehicle market share (Chakraborty et al., 2022; Falchetta & Noussan, 2021; IEA, 2021; Jenn & Highleyman, 2022). However, in Asian countries such as India, Indonesia, Taiwan

CONTACT Chandra Balijepalli n.c.balijepalli@leeds.ac.uk Institute for Transport Studies, University of Leeds, UK

and Vietnam, motorised two-wheeler is the most dominant mode of travel due to its affordability and flexibility (Guerra, 2019). Thus, countries such as China, Taiwan, Vietnam have been in the forefront of adopting their policies to promote electric two-wheeled vehicles (Chen et al., 2021; Huu & Ngoc, 2021; Qin et al., 2021; Sovacool et al., 2019). It will be essential to understand how electric motorcycle might match the competing conventional motorcycle and, indeed, how may we assist the adoption towards battery operated electric vehicles.

Choice modelling studies on electric motorcycle preferences have been done before (Chen et al., 2021; Filippini et al., 2021; Guerra, 2019; Scorrano & Danielis, 2021; Sovacool et al., 2019) but most of them focused on attitudes/behavioural motivations, but none had explicitly focused on battery technology attributes. The battery vehicle technology is a rapidly growing body of research with several advancements taking place in a short space of time. This study adopts the latest notions on charging methods available (e.g. battery swaps, quick charging methods) and contributes to the growing body of research in several ways. First, the study analyses the potential of electric motorcycle uptake in Bandung City in Indonesia, where nearly three quarters of traffic is constituted by motorcycles. Secondly, keeping in view the latest developments in battery technology, this study includes new options of charging methods in the choice experiment, such as battery swap at home/station, and super-quick charging at station, as an alternative to the standard plug-in at home/office. This emphasis on charging methods distinguishes this study and complements the earlier work by Guerra (2019) and Sovacool et al. (2019) who focused on charging duration.

The overall aim of the research is to assess the ability of electric motorcycles in penetrating the market, and the particular objectives of the study are two-fold: (i) to assess the preferences of consumers considering the performance, purchase price, operating cost of electric two-wheelers; and (ii) to review the governmental policies, regulations and the availability of infrastructure to support their operation. The specific objective of the paper is to analyse the consumer preferences based on a stated preference survey of over 700 respondents in Bandung, Indonesia where motorcycle is the dominant mode of transport. The paper describes the estimated choice models, namely Multinomial Logit and Mixed Multinomial Logit to assess the consumer preferences and how they value the attributes of electric motorcycles and battery charging methods. An understanding of the key determinants of electric motorcycle uptake will help the motorcycle developers in adjusting the motorcycle performance too.

This paper is divided into seven sections including this one. Section 2 reviews the literature, and Section 3 specifies the methods used. Section 4 describes the survey conducted. Section 5 analyses and interprets the results. Section 6 describes the implications to policy and Section 7 concludes the work.

2. Literature review

In this section, we review the uptake of electric two-wheelers around the world with an intent to identifying the factors that had contributed to the success or failure of the initiatives. As such, the review is divided into two parts, the first addressing the factors in policy space while the second looking at the attributes of electric vehicle.

2.1 Conventional motorcycle restriction and electric motorcycle subsidies as policy instruments

In China, the electric two-wheeler (existing in different forms – electric bikes or e-bikes, electric motorcycles) has been in use for over two decades. Fishman and Cherry (2016) describes many e-bikes as resembling bicycles and others as like large gasoline scooters, though with similar underlying technology with a top operating speed of 30kph. According to Yang (2010), China has been experiencing significant growth in electric motorcycles since 1998 which is caused by policies imposed by the government though inadvertently. The boom of e-bike sales was caused mainly by the motorcycle ban in many areas by the Chinese government. Widespread motorcycle bans were introduced by several local authorities to reduce traffic congestion, air pollution and accident rates. However, the regulatory framework in force means, e-bike was not categorised as a motor vehicle. Thus, people using e-bikes could easily overcome the restrictive policy banning the conventional motorcycles. Weak enforcement of standards also helped the electric two-wheeler market further which resulted in a boom in their numbers from a mere 56,000 in 1998 to 21 million in just 10 years, though mainly of low powered e-bikes. However, the policy at regional level is inconsistent which makes the future of electric two-wheeler uncertain in China. Thus, the boom in electric vehicle numbers in China is sometimes dubbed as a 'policy accident' rather than a 'policy success'.

The case of Taiwan is completely different to that of China. Taiwan made a conscious effort, persistently over a number of decades to promote electric scooters, firstly, to sustain the oil shock in the 90's and then to improve the air quality in cities in the new millennium. Instead of adopting a regulatory approach, they relied on subsidy as a strategy to promote e-scooters. As explained by Yang (2010), the Taiwanese government started to support the use of electric motorcycle in 1998 by providing a large sum of money NT$ 1.8 million (approximately US$10 million) as subsidy. The subsidy was offered in a number of forms e.g. tax reduction for electric motorcycle manufacturers, R&D, marketing programme, charging infrastructure and purchase price. The subsidy policy was quite successful as the sales went up by 8.79 times from 1500 in 1998 to 13,000 vehicles in year 2000 (+779%). However, inconsistent quality of vehicle and inadequate maintenance facilities quickly dampened the e-scooter sales that led to a suspension of the subsidy programme.

Vietnam has a high motorcycle population (>90% of total number of vehicles) and can potentially benefit from adopting e-scooters to reduce the air pollution. A stated preference experiment found that consumers are highly sensitive to fuel prices though they discount the fuel cost savings at much higher rates (up to 40%) due to the uncertainty involved (Jones et al., 2013). Superior technology of e-scooters is valued at VND 10 million which implies that if better technology is delivered at cheaper prices, the adoption rate will significantly improve. Finally, consumers are willing to pay VND 1.64 million to avoid sales tax of one million. This equates to reducing the recharge time by 3.5 h or increasing the range by 90 km. Thus, incentivising the consumers is likely to help boosting the e-scooter sales by a significant margin.

Wang et al. (2019) carried out a study to analyse what factors that contribute significantly to the market share of electric vehicles. The study collected year 2015 data from 30 different countries around the world. A range of variables including financial incentives and non-financial incentives were analysed, to identify the most significant factors. Interestingly, the study concluded that the factors that are statistically significant in predicting the market share are: i) road access priority, ii) charging infrastructure density (number of available charging stations) and iii) fuel price. Road access priority, such as access to dedicated bus lane or high occupancy vehicle lane, according to the study is deemed the most significant factor, in addition to the charging infrastructure and fuel price variables. In addition to this, Scorrano and Danielis (2021) mentioned that policies related to circulation tax and insurance premium are also significant in influencing people's decision to buy e-scooters.

2.2 Electric vehicle attributes

Yang (2010) explains, one should not assume that, if the price of electric motorcycle is comparable to gasoline-powered motorcycle, the electric motorcycle could compete in the market. Price is certainly important for a successful market penetration of a product, but other factors could also be highly significant. For instance, the charging method of electric motorcycle, such as plug-ins which require long charge duration may not be acceptable to the purchaser. The availability of charging facilities and infrastructure will also influence preferences towards electric motorcycles. As mentioned by (Hwang, 2010; Yang, 2010), one of the factors that contributed to the failure of electric motorcycle in Taiwan was the weak technology which was reported by many users.

Despite the failure experienced in 1990s, the effort by Taiwanese Government to support the electric motorcycle implementation continued in 2009 (Hwang, 2010). The government carried out a new study to understand factors that caused the earlier failure. The study found that the electric motorcycle performance in year 2003 in terms of maximum speed, acceleration and climbing ability were acceptable. However, the electric motorcycle performance/specification fell short in several other aspects. Hwang (2010) then concluded that the aspects which are the most significant for peoples' disinterest in electric motorcycle are (i) lengthy charging duration and short travel distance per charging (range), (ii) low battery durability resulting in high average operational cost and (iii) insufficient charging infrastructure.

The Taiwanese government, from the study by Hwang (2010), concluded that several innovations are needed to avoid the failure of 1998–2003. The first is the advancement of battery technology (higher capacity) with longer travel distance per charging. This can be achieved by using Li-ion battery rather than valve regulated lead-acid (VRLA) battery. The second is the application of battery exchange system to avoid lengthy charging duration. Thus, Taiwan decided to subsidise electric motorcycles with detachable Li-ion battery pack and not the one with the fixed VRLA battery.

The case for shorter charging duration is further strengthened by Levinson and West (2018), which analysed the difference in sales, fuel consumption and emission amount, from year 2017 to 2050, by varying the number of 'level 2'charging stations and DC fast charging stations. The charging stations differ in terms of charging duration with DC fast charging, as its name implies, has shorter charging duration. The study concluded that, on a large-scale deployment, the injection of public DC fast charger is more effective compared to public 'level 2' charger in terms of increasing sales, distance travelled by electric vehicles (electrified mileage) and reducing greenhouse gas emissions. Neaimeh et al. (2017) analysed the data from 35 battery electric cars in the UK for 12,700 driving days and explored the travel distance relationship with standard and fast charger. The study found that fast charger enables electric vehicle to travel more distance per charging than that achieved by using a standard charger. This makes electric vehicles more attractive to potential adopters and gives a sense of security in terms of the distance the electric vehicle can travel. Finally, Guerra (2019) and Sovacool et al. (2019) considered charging duration though none had focused on charging methods including battery swaps.

3. Modelling methods

This study uses two models to estimate motorcycle choice probabilities, standard multinomial logit and mixed logit model. Brief explanation of the theory, as well as estimated parameters by using the two models are described below.

The mixed logit (or Mixed Multinomial Logit model, MMNL) is currently one of the most widespread models for modelling discrete choice in the context of a stated preference survey. In what follows, we broadly describe the basic model, mainly for brevity reasons, but describe in detail the preference space approach used in this paper contrasting it from the standard willingness to pay space approach. Discrete choice models help assessing the behaviour of respondents establishing a point of indifference above which the positive preference space lies. Whilst these models are well-used in practice, it is worth noting that they suffer from cognitive difficulty associated with multiple complex choices, thus making good survey design as an essential input for generating useful results. We refer the interested reader to Train (2009) for further insights into choice modelling.

Let U_{int} be the utility that respondent n derives from alternative i in choice situation t. It is made up of a modelled component V_{nit} as well as a random i.i.d component $\in_{int}$ which follows a type 1 extreme value distribution. We have:

$$U_{int} = V_{int} + \in_{int} \tag{1}$$

$$V_{int} = ASC_i + \beta_n^{'} x_{int} \tag{2}$$

where, ASC_i is the Alternative Specific Constant for alternative i, β_n is a vector of taste parameters and x_{int} is a vector of attribute and attribute values for alternative i. Furthermore, we note that the ASC is included for all but one of the alternatives (the choice of which is arbitrary). As a result, the probability that respondent n chooses a given alternative i conditional on β_n and the ASC in choice situation t corresponds to the MNL probabilities given by:

$$P_{int}(\beta_n) = \frac{exp^{V_{int}}}{\sum_{j=1}^{J} exp^{V_{jnt}}} \tag{3}$$

The elements in β_n can be allowed to vary randomly across respondents, using a joint distribution $f(\beta_n|\Omega)$ where Ω is a vector of parameters to be estimated, relating to the means and covariance structure of the elements in β_n. More precisely, for each of the k elements in β_n, we use the following specification:

$$\beta_{kn} = \mu_k + \sigma_k \zeta_{kn} \tag{4}$$

where, μ_k corresponds to the mean and σ_k the standard deviation of the random parameter. A Multinomial Logit (MNL) model is simply a model where the parameters labelled as σ are *constrained to zero*, thus the MNL model is a special case of the MMNL model shown in Equation (4). The parameter ζ_{kn} is a random disturbance which is distributed N(0,1) in the context of this paper. As the actual value of β_n for a given respondent is not observed by the analyst, the choice probabilities are given by a multi-dimensional integral of the MNL probabilities described above. The probability of the sequence of choices observed for person n is given by:

$$L_{nt} = {}_{\beta_n} \prod_{t=1}^{T} P_{nt}(\beta_n) f(\beta_n | \Omega) \delta\beta \tag{5}$$

where, P_{nt} corresponds to the probability of respondent n choosing the alternative that was *actually* observed to choose. These probabilities are estimated by maximum likelihood methods in practice.

Modelling in preference space vs WTP space

In this study, we estimate our models in *Preference Space* as opposed to the *Willingness-To-Pay* (WTP) Space specification described by Scarpa et al. (2008), among others. Although we are mainly interested in deriving welfare (*i.e.* willingness-to-pay) estimates and distributions for each of the non-monetary attributes considered, preliminary models have revealed that the Preference Space approach fits the data better than the WTP space approach for this particular dataset. In addition, local optima issues were experienced when estimating models in WTP space. The chosen modelling strategy allows for different distributional assumptions for the marginal WTP while at the same time preventing estimated implicit prices to 'explode', which is commonly found when using a negative log-normal or negative log-uniform distribution for the monetary parameters of a model. A more detailed and comprehensive discussion on this topic is available in Crastes Dit Sourd (2023).

As it is well-known, in Preference Space, welfare measures are obtained by sampling a large number of draws from the distribution of a given non-monetary attribute and dividing each draw by a different draw sampled from the distribution of the monetary attribute. Certain distributions used for the monetary attribute such as the log-normal distribution have a point mass at zero, which can mechanically lead to implausibly large WTP estimates. In this paper, we specify the *purchase price* and *operational cost* attributes to be (negative) log-normally distributed but we use mixture distributions (Fosgerau & Mabit, 2013) where the second-order polynomial is constrained to be positive in order to shift the point mass of the distribution away from zero. More precisely, purchase *price* and *operational cost* distributions are specified as follows:

$$\beta_{purchase\,price,n} = -\exp\begin{pmatrix} (\mu_{purchase\,price,n} + \sigma 1_{purchase\,price,n} \zeta_{purchase\,price,n} \\ + \exp\left(\sigma 1_{purchase\,price,n}\right)\left(\zeta_{purchase\,price,n}\right)^2 \end{pmatrix} \tag{6}$$

$$\beta_{operational\,cost,n} = -\exp\left(\begin{array}{l}(\mu_{operational\,cost,n} + \sigma 1_{operational\,cost,n}\zeta_{operational\,cost,n} \\ + \exp\left(\sigma 1_{operational\,cost,n}\right)\left(\zeta_{operational\,cost,n}\right)^2\end{array}\right) \tag{7}$$

The constrained mixture distribution approach, which has never been used elsewhere to the best of our knowledge, yields reasonable welfare estimates (with respect to the literature and competing models estimated on the same data) while also allowing for randomly distributed monetary attributes. This approach is somewhat different from the proposition of Crastes Dit Sourd (2023) for shifting the point-mass of the negative log-normal away from zero in the sense that it relies on the use of a constrained mixture of normal distributions for the price instead of using a μ-shifted normal distribution. Whether the two approaches perform differently is out-of-the scope of the paper but is an interesting prospect for future work on this topic. Results for MNL model and MMNL model are reported in the next section.

4. Study area and data collection

4.1 Study area

Indonesia is one of the developing countries that has been experiencing problems with high transport emissions. This is prevalent in big metropolitan cities in Indonesia such as Jakarta, Surabaya and Bandung (Farda & Lubis, 2018). Bandung City located in West Java, Indonesia is one of the most populous cities in Indonesia. According to Bandung City statistics, in 2017, Bandung City is inhibited by 2,497,938 residents. The city has 30 districts with a total area of 167.31Sq Km. Bandung City has 1.8 million vehicles (in 2017) and motorcycles and cars are the dominant modes (Figure 1). Given the proportions of vehicles, based on fuel efficiency and an assumed average annual trip length for each vehicle category we can estimate that the fuel consumption of motorbikes in the cities in Indonesia is at least five times that of cars, and so are the emissions. This strengthens the case to shift to electric motorcycles.

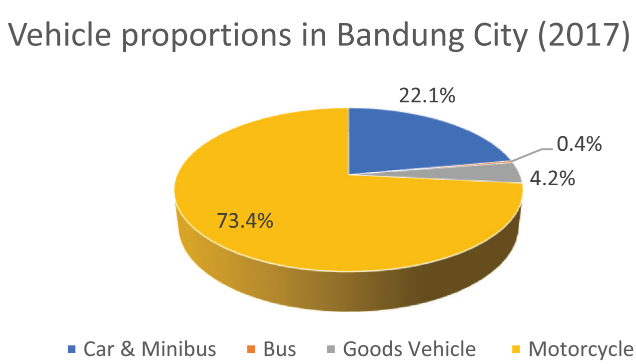

Figure 1. Vehicle proportions in Bandung City. Note: (Bandung City Central Bureau of Statistics, 2018)

4.2 Initial survey

To develop a choice model which is used to estimate the uptake of electric motorcycle in Bandung, a survey to capture peoples' preferences towards motorcycle was carried out. However, before launching the full-scale stated preference survey, an initial survey was done to understand the factors that matter to the people when buying a motorcycle. In the survey, a long list of 15 attributes (Table 1) that influence people when choosing a motorcycle, were adopted from the past studies, e.g. Jones et al. (2013), Guerra (2019).

During the initial survey, 92 randomly chosen respondents were asked to rank the attributes which influence them the most when choosing an electric motorcycle (Sample representativeness confirmed by Chi-square test though not reported here). The frequency of respondent choices for each attribute was then used to rank the most significant to the least significant from a respondent perspective. Top seven attributes reflecting the response frequency were shortlisted for the stated preference survey design. The shortlisted attributes were: (i) purchase price, (ii) operational cost, (iii) range per charging, (iv) charging duration, (v) maximum speed, (vi) charging method and (vii) ownership tax.

4.3 Stated preference survey questionnaire and attribute levels

A stated preference survey questionnaire was designed with three sections: (i) socio-demographic characteristics, (ii) travel characteristics and (iii) stated preference survey. These sections were featured in both the pilot survey as well as the main survey.

- *Respondent profile*: This section of the questionnaire collects data on age, gender, occupation, education and income level.
- *Travel characteristics*: Respondent travel characteristics include, monthly transport expenditure, number of motorcycles owned, number of trips made by using motorcycle, travel distance and travel purpose.
- *Stated preference choice sets*: The last section of the questionnaire consists of a series of 14 choice tasks. The choice situations were generated based on discrete combinations of attribute levels which followed the Efficient Design procedure (Rose & Bliemer, 2009).

Table 1. Longlisted attributes for the initial survey.

No	Attribute
1	Purchase price
2	Speed
3	Range/charging
4	Operating cost
5	Style
6	Spare parts availability (battery/engine)
7	Acceleration
8	Braking deceleration
9	Emission level
10	Charging duration
11	Charging method
12	Ownership tax
13	Motorcycle weight
14	Maintenance facility availability
15	Used motorcycle selling price

Table 2. Attribute levels for the stated preference survey.

Attribute	Electric Motorcycle (EM)	Automatic Scooter (AS)
Purchase price (IDR million*)	16, 20, 23	16, 20, 28
Operational cost (IDR/100Km)	7500, 9500, 13500	19000, 22500, 27000
Range per charging (Km)	30, 60, 90	200, 300, 360
Maximum speed (Km/h)	60, 90, 120	60, 90, 120
Charging method	Base: Plug in – home/workplace Method 1: Battery swap–station Method 2: Battery swap-home Method 3: Recharge-station (10 min)	Station refueling

*Note: $1USD ~ 15000 IDR.

The attribute levels included in the survey were chosen based on a series of pre-tests. In particular, the range of *purchase price* and *operational cost* attributes were explored. This was found necessary after pre-tests which showed that the initial ranges assumed were too low, leading most respondents to give low weight to these attributes, thus leading to implausibly high willingness-to-pay values. The final set of attributes and their levels for electric motorcycle as incorporated into the survey design alongside of the standard alternative automatic scooter available in the market which runs on gasoline are shown in Table 2.

4.4 Stated preference survey

The main survey collected 703 responses from randomly chosen persons with different ages and gender after obtaining their consent to participate in the survey. No individual identifiable data was collected. Respondents were assisted with pictures on the charging method to make sure that they understand the survey question. The data collected during the survey is then used to develop choice models to predict the uptake of electric motorcycle based on the value of its attributes.

5. Results and discussion

5.1 Survey results

From the returned questionnaires, 40 incomplete forms (5.7%) were excluded reducing the total usable sample to 663 observations. No specific pattern has been identified in the omitted samples. In other words, we have not found that any specific group was more likely to not fill the survey properly. Thus, this does not affect the representativeness of our survey sample. Moreover, the total number of participants included in the analysis is sufficiently large and the results were found statistically significant.

5.2 Socio-economic and travel characteristics

The main stated preference survey captured respondents' socio-economic and travel characteristics which are summarised in Table 3. Most of the respondents (44%) are within the age group of 18 to 30. In terms of occupation and education levels, most of the respondents work as an entrepreneur (32%) and have high school as their highest education level (56%). 60% of the residents have earnings of up to 5 million

Table 3. Respondent Socio-Economic characteristics (left) and travel characteristics (right) ($N = 663$).

Socio-Economic -Characteristics	Number	Percentage	Travel Characteristics	Number	Percentage
Age			**Monthly transport expenditure (IDR)**		
18–30	294	44%	less than 125,000	110	17%
31–39	137	21%	125,001–375,000	308	46%
40–49	133	20%	375,001–625,000	156	24%
more than or equal to 50	99	15%	625,001–1,250,000	50	8%
Gender			1,250,001–1,875,000	22	3%
Male	298	45%	more than 1,875,000	17	3%
Female	365	55%	**Number of owned motorcycles**		
Occupation			0	6	1%
Student	133	20%	1	400	60%
Government Employee	85	13%	2	198	30%
State/Private Owned Enterprise Staff	121	18%	more than 2	59	9%
Entrepreneur	214	32%	**Number of motorcycle trip in a day (weekday)**		
Pensioner	17	3%	0	3	0%
Others	93	14%	1	14	2%
Education Level			2–3	443	67%
Uneducated	11	2%	4–5	129	19%
Elementary School	44	7%	more than 5	74	11%
High School	373	56%	**Plan to buy a motorcycle in the next three years?**		
College/University	213	32%	Yes	442	67%
Post-Graduate	22	3%	No	221	33%
Average monthly income (IDR)			**Type of preferred motorcycle (new or second hand)?**		
less than 1,000,000	121	18%	New	562	85%
1000,000–3,000,000	192	29%	Second Hand	101	15%
3,000,001–5,000,000	204	31%	**Minimum Value for Trade-Ins**		
5,000,001–10,000,000	112	17%	<20% purchase price	48	7%
10,000,001–15,000,000	20	3%	21–40% purchase price	186	28%
more than 15,000,000	14	2%	41–60 % purchase price	275	41%
			61–80% purchase price	154	23%

rupiahs per month ($1USD ~15000 IDR) with about half of them earning up to 3 million rupiahs per month. In order to verify the representativeness of the sample, we have undertaken Chi-square test of independence and rejected the null hypothesis in all cases (<<p-value) that the observed sample is not dependent on the population distribution expected (see Appendix).

Regarding travel characteristics, 46% of the respondents spend between 125 thousand and 375 thousand rupiahs on transport per month. A large portion of the respondents own only one motorcycle (60%) and carry out 2–3 trips during weekday by using motorcycle (67%). Most of them are planning to buy a motorcycle in the next three years (67%) and prefer to buy a new one (85%) rather than a used one. If a trade-in scheme is implemented, most of the respondents (41%) expect the minimum value for trade-ins at 41% to 60% of the purchase price.

Figure 2 shows the travel purpose and Figure 3 indicates the travel distances. The average travel distance for a weekday trip is 8.7 km compared to 7.9 km for a weekend trip though some are longer than 15 km.

We also learn from the survey that most respondents appear to prefer purchase price incentive (51%) followed by annual motorcycle tax incentives (17%). Figure 4 shows the preferences for other types of incentives considered in addition in the research.

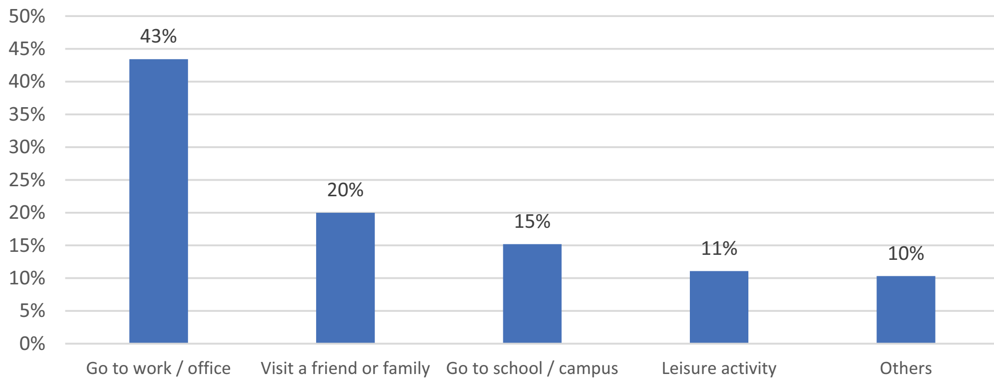

Figure 2. Respondent travel purpose.

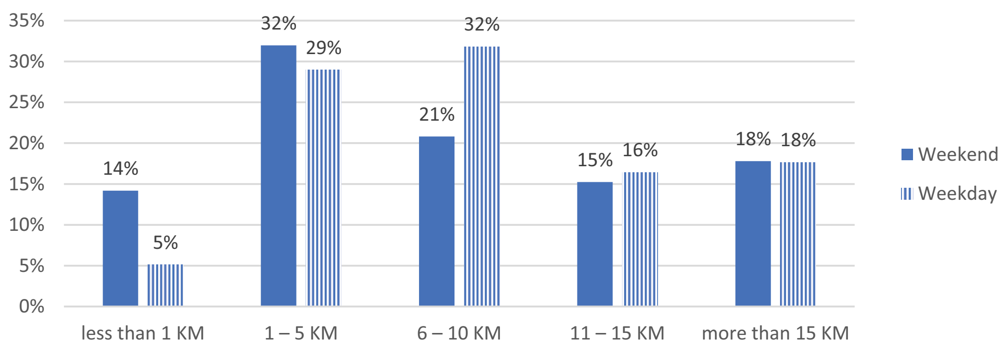

Figure 3. Respondent travel distance.

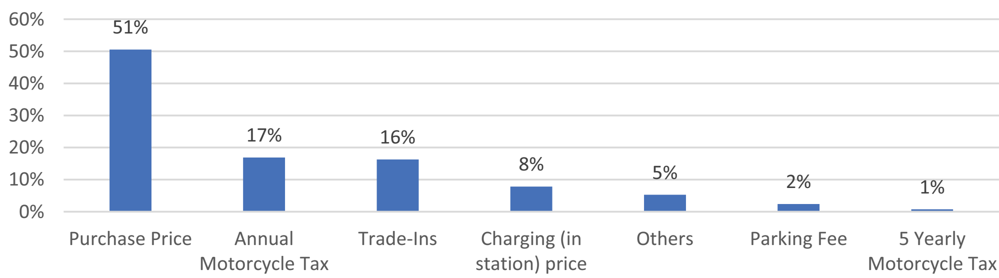

Figure 4. E-motorcycle incentives preferred by the respondents.

5.3 Estimation results

5.3.1 Modelling results

In this section, we first provide details on the distributions used for modelling random heterogeneity in the MMNL model as well as the scaling of the variables. Indeed, the different attributes entering the model are all expressed in different units (Km/h, monetary units, etc) which all have different orders of magnitude. This can affect model convergence. Preliminary models have been estimated in order to find the right

Table 4. Scaling and distributional assumptions.

Attribute	Scaling	Distribution
Purchase price	/1000	Negative log-normal
Operating cost	/100000	Negative log-normal
Range	/1000	Positive log-normal
Speed	/100	Normal
Charging method	NA	Normal
ASC	NA	Normal

scaling for each one of the attributes. Scaling and distributional assumptions are reported in Table 4.

Furthermore, we enrich our models by assuming different sensitivities for *Purchase price*, *Operational cost* and *Range* depending on the type of vehicle. This is motivated by the fact that these attributes had very different ranges in the stated preference survey. It is common to allow for different sensitivities for the same attribute depending on the alternative, see for example Fosgerau and Bierlaire (2009). A marginal increase in range for an EM might be worth more than a marginal increase in range for an AS all else being equal, given that the EM has a more limited range than the AS, as may be noted from Table 2 earlier. In other words, consumers might value more an increase in range for a vehicle for which the overall range is more limited. The parameter estimation results for the MMNL model are summarised in Table 5.

We first investigate whether the MMNL model (Model B) is better than an MNL model without random heterogeneity in preferences (Model A) by conducting a likelihood ratio-test. Results of the tests are reported in Table 6 below.

Table 5. Model results.

	Model A - MNL				Model B - MMNL			
Log-Likelihood (final)	−6342.286				−6063.739			
AIC	12706.57				12183.48			
BIC	12785.07				12383.28			
	AS		EM		AS		EM	
	Param.	Rob. T.	Param.	Rob. T.	Param.	Rob. T.	Param.	Rob. T.
βPrice	0.762	3.28	1.619	9.16	0.821	3.10	1.741	9.44
βCost	1.854	16.33	1.375	5.93	1.626	7.76	1.059	2.43
βRange	0.945	6.86	2.146	14.74	1.070	7.00	2.139	11.60
βSpeed	0.245	3.41	0.245	3.41	0.185	2.05	0.185	2.05
βMethod1	.	.	0.440	5.24	.	.	0.400	4.11
βMethod2	.	.	0.137	1.82	.	.	0.009	0.10
βMethod3	.	.	0.492	6.98	.	.	0.553	6.60
βASC	−0.478	−1.87	.	.	−0.451	−1.66	.	.
σPrice1					−0.362	−3.48	−0.033	−1.10
σCost1					0.227	3.98	−0.206	−2.04
σPrice2					−6.854	−5.81	−6.378	−7.53
σCost2					−1.348	−6.59	−1.715	−4.04
σRange					−0.011	−0.24	−0.561	−5.36
σSpeed					0.052	1.01	0.052	1.01
σMethod1					.	.	0.557	4.91
σMethod2					.	.	−0.139	−1.14
σMethod3					.	.	−0.711	−6.70
σASC					0.062	1.67	.	.

Table 6. Likelihood ratio test.

Likelihood ratio test-value	553.1
Degrees of freedom	15
Likelihood ratio test p-value	0

Results of the test indicate that the mode with random heterogeneity in preferences fit the data better than the (more restricted) MNL model. This result is unsurprising but confirms that Model B is the ‘better’ model. However, the relative values of the parameters in both models indicate that they yield similar results, although Model B obviously provides richer insights. Results from another (unreported model) where the various parameters are assumed to follow a classic negative log-normal distribution (instead of the mixture distributions introduced in section 3) show that Model B is an improvement over a more classic specification for which the log-likelihood was found to be −6074.244.

Results indicate that all the attributes significantly affect preferences. Given that most of the parameters are constrained to be either positive or negative, investigating whether the parameters have the right sign is of limited use. A few exceptions are *Speed*, which is found to be positive as expected (meaning that a faster EM or AS is more desirable than a slower one) and *Charging methods*. The values and signs of the different *Charging Method* parameters indicate that *Method 1 (Battery swap, station)* and *Method 3 (Recharge at station, 10 minutes*) are preferred over the base charging method (*Plug-in home/workplace*). On the other hand, respondents are indifferent between the base charging method and *Method 2 (Battery swap – home)* which is unsurprising given that this is very close to plugging-in the vehicle. Finally, the negative ASC indicates that respondents are less likely to choose the AS over the EM all else being equal.This analysis can be refined by looking at WTP estimates instead of parameter values.

5.3.2 Welfare estimates

The WTP distributions are reported in Table 7 below and shown in Figure 5.

Results from Table 7 are *marginal willingness-to-pay measures*, that is the WTP for a marginal increase in the value for a given attribute. The introduction of a constrained mixture of normal for the monetary attributes is found to be successful in the sense that it yields welfare estimates which are in line with the MNL model values, which is a result which is rarely obtained in the literature. The results should be interpreted as such: a marginal increase in range for AS is found to be worth 0.14 millions of IDR compared

Table 7. Willingness-to-pay distributions (in millions of IDR).

Attribute		Min.	1st Qu.	Median	Mean	MNL	3rd Qu.	Max.
Range	*AS*	0.02	0.10	0.13	**0.14**	**0.12**	0.16	0.89
	EM	0.01	0.10	0.15	**0.17**	**0.17**	0.22	2.09
Speed	*AS*	−0.05	0.06	0.08	**0.09**	**0.11**	0.11	0.65
	EM	−0.01	0.03	0.03	**0.03**	**0.05**	0.04	0.08
Charging method	*1*	−45.28	0.43	6.99	**7.01**	**8.71**	13.58	55.70
	2	−14.55	−1.50	0.14	**0.15**	**2.71**	1.79	11.68
	3	−50.38	1.28	9.66	**9.68**	**9.75**	18.05	68.69
AS (constant)		−128.55	−25.53	−19.68	**−21.16**	**−22.33**	−15.13	−3.12

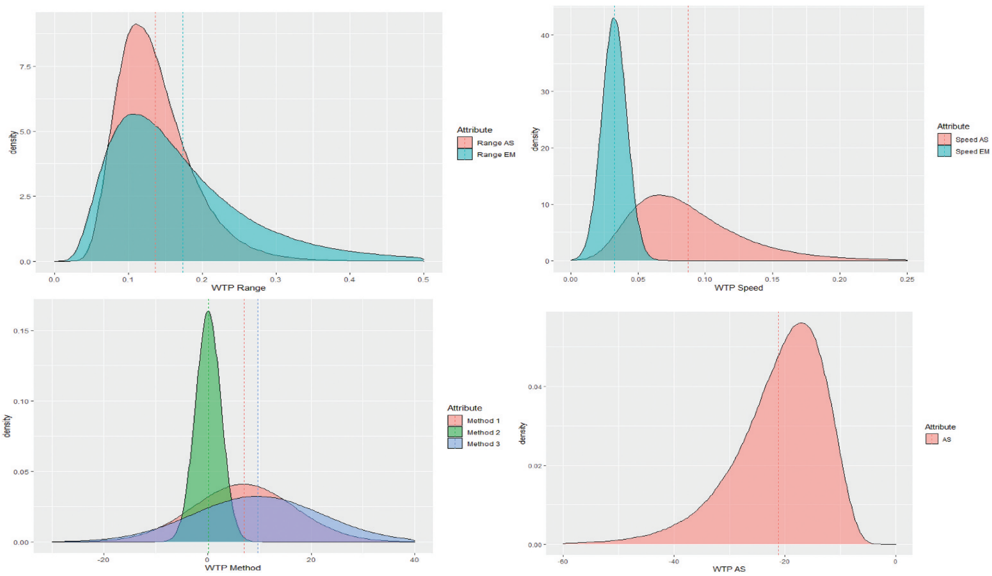

Figure 5. Willingness-to-pay distributions.

to 0.17 millions of IDR for EM. This means respondents prefer higher range on EM more than that on the AS. Or in other words, the users perceive that the range for an EM is more valuable than that for an AS.

Charging method seems to be the most critical as perceived by the respondents which is evident from the results in that the WTP is the highest amongst the three attributes – range, speed and charging method. Within the charging methods, they prefer *Method 3 (Recharge at station, 10 minutes)* the most (highest WTP) and *Method 2 (Battery swap – home)* the least (lowest WTP) with a value which is not significantly different from *charging at home*. These results indicate that respondents are willing-to-pay 7.01 million IDR for swapping the battery of an EM at a station instead of charging it at home, and 9.68 million IDR for charging their EM at a recharge station.

Speed seems the least concerning attribute to the respondents as their WTP is the minimum amongst the attributes – range, speed and charging method. This is unsurprising in the context of Bandung where the traffic congestion is very high all over the day.

It is worth noting that these are mean WTP estimates and that different distributions offer a diverse range of preferences, as illustrated by Figure 5. We note that the distributions of *Speed* are very different between EM and AS and that the two curves barely overlap, which suggests that respondents have different expectations regarding the two vehicles. Respondents are less concerned about the EM being slow in comparison to the AS. On the other hand, respondents are willing-to-pay for a marginal increase in *Range* for the EM than for the AS. As previously discussed, this could be because the autonomy of the EM is more limited, so any additional km of range is more valuable. Other results show that the distribution of the value of the AS compared to EM is very skewed to the right (WTP AS), which means that respondents are willing-to-pay to switch from an AS to an EM all else being equal. We also find that the WTP distribution for *charging method 2* is much narrower than the distributions for the other methods, which suggests that consumers' preferences are more heterogeneous when it comes to *charging method 1* and *3*. In other words, most consumers dislike *charging method 2* while their preferences for the other methods are more mixed.

We now compare our findings with Guerra (2019) who had conducted a stated preference experiment to assess the factors affecting choice of EMs in Solo, Indonesia. We note that they have reported WTP values of 13.1%, 7.8% and 7.4% (as percentage of purchase price) for the attributes – charge time, speed and range respectively. The aim of this comparison is to analyse to what extent the WTP values from the two independently conducted studies align with each other to indicate the generalisability of the results. In terms of charging time, Method 3 is the only one in our study that involves charging within a time period (10 min) and with the other two methods, the duration is irrelevant. The WTP by Method 3 in Table 7 divided by six makes it comparable with 'an hour shorter charge time' which results in a WTP of 8.2% of the average purchase price of 19.67 million IDR per EM. In terms of speed, the WTP for EM in Table 7 should be multiplied by 10 to bring it to a similar scale as '10 km/h faster' resulting in a value of 1.5% of the purchase price per EM. Finally, the range for EM in Table 7 should be multiplied by 10 to make it comparable, which results in a value of 8.6% of the purchase price per EM.

Firstly, it is interesting to note that between the two cities of Bandung and Solo, consumers perceive that the charge time is the most critical as indicated by the highest WTP in absolute terms (IDR 9.68 million in Bandung vs IDR 2.35 million in Solo) among other attributes. However, in relative terms, the WTP for charge time in Bandung (8.2%) seems to be slightly lower compared to that in Solo (13.1%). Given the differences between charging methods in the two studies – 10 min superfast charging vs standard charging up to 5hrs, and the fact that the down payment did not enter the Solo model, the WTP values between the two studies may not be significantly different to each other. Secondly, the WTP for a marginal increase in speed of EM in Bandung (1.5%) is about five times smaller than the WTP in Solo (7.8%), which perhaps reflects the differences in traffic conditions and the terrain between the two cities. While Solo has a flat distribution of traffic over its grid network, Bandung has a highly peaked distribution of traffic on a semi-circular network with very hilly terrain, due to which residents of Bandung might have perceived a marginal increase in speed as not valuable. Finally, the WTP for a marginal increase in range is very similar between Solo (7.4%) and Bandung (8.6%). Of course, the results between the two cities could be compared further by estimating the same models for the two samples using similar scaling for different parameters, but this is beyond the scope of the current paper.

6. Implications to the policy

This study has major implications to the policy making on electric motorcycles in Indonesia which are described as below:

- Firstly, the results clearly indicate the preference for quick charging at station or battery swap at the station over the plug-in at home/work. Thus, the government may promote the network of battery swap/quick charging stations by offering suitable subsidies to attract investors/operators. This can also generate employment for the youth.
- Secondly, range of electric motorcycle seems to attract high willingness to pay, thus, implying that the respondents prefer to have a higher range per charge of the battery. This indicates the need for investing in improving the battery technology further in terms of the range that it can offer. The government may invest in R&D of the battery technology by launching funded research through local/international academia.
- Finally, local governments may promote the use of electric motorcycles by reducing local taxes and also by exempting them from road user charging schemes (e.g. parking fees). Wider traffic management schemes aimed at reducing pollution levels in city centre-areas can exempt electric motorcycles too.

7. Concluding remarks

The issue of air pollution has become the main concern in big cities around the world. The impact of air pollution is severe and corrective actions need to be taken to prevent the problem from getting worse. Electric vehicle is viewed as a means to support the aim of meeting the UN's Sustainable Development Goals. In Indonesian cities such as Jakarta, Surabaya, Bandung and Medan, the vehicle population has been increasing rapidly due to the increase of population. A large proportion of those vehicles is motorcycles due to the easy affordability and flexibility that they offer. Large motorcycle fleet also means high pollutant emissions and compromised road safety. Opportunities thus exist to promote electric motorcycles.

To identify the factors/attributes influencing electric motorcycle choice, this study uses the choice modelling method based on 663 stated preference survey questionnaires which are collected in different places within Bandung City. Based on this data, model parameters are estimated by using the standard MNL model and mixed logit model. For the charging method, the 'plug-in home/work' is used as a base case for the charging method parameter estimation. The main conclusions from this work are summarised below.

The modelling work indicates 'recharge station 10 min' and 'battery swap-station' as the two most preferred methods. Thus, to promote the electric motorcycle adoption, investment strategy involving quick recharge/battery swap stations would help at least to meet the short/medium term needs. Secondly, the range appears to be very important as perceived by consumers, and, thus, improvement in battery technology will go a long way in supporting the uptake of electric motorcycles. Finally, use of a constrained mixture for the distribution of monetary attributes in the MMNL model found to be a useful innovation. This approach allowed to derive reasonable marginal WTP measures compared to the values derived from a corresponding MNL model. Furthermore, WTP values are lower than those typically found with a log-normally distributed monetary attribute while at the same time ensuring a better goodness of fit. This is a useful alternative to estimating a model in WTP-space, an approach which is often found to provide inferior goodness-of-fit because of the implied distributional assumptions on marginal WTP.

The sample size in this survey is sufficiently large, however, we note that high-earning motorcycle drivers were hard to find as they largely own/drive cars. Perhaps, it matters less for the uptake of electric motorcycles in Indonesia, but in the general case of electric vehicles (i.e. car and motorcycle) it will certainly matter which will need redesigning the survey. Indonesian government appears to have taken e-motorcycles as a priority in their stride towards meeting the UN's Sustainable Development Goals. They have started developing strategic directives to promote the uptake of e-motorcycles in various provinces across the country. It is hoped that the results of this study will be found useful by regional bodies who are expected to translate the high-level directives into local practice.

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Author contributions

CB: Conceptualisation, writing – original draft, writing – review & editing, supervision, project administration, funding acquisition
SS: Conceptualisation, writing – review & editing, supervision
RCdS: SP survey design, analysis
MF: Survey execution, analysis, writing – original draft
TP: Survey execution, analysis
HL: Supervision, project liaison, funding acquisition

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Appendix

Chi-square test of independence of survey sample

Respondent Characteristics	Proportion in the population#	Expected (Sample size × proportion in the population)	Observed Value (Based on the Survey)	Chi-Square Test	
Age					
18–30	37.1%	246	294	p- Value	6.4823E–07
31–39	21.4%	142	137	Null Hypothesis	rejected
40–49	18.1%	121	133		
more than or equal to 50	23.4%	156	99		
Gender					
Male	50%	334	298	p- Value	0.00586161
Female	50%	330	365	Null Hypothesis	rejected
Income Level					
less than 1,000,000	21%	140	121	p- Value	5.0468E–12
1000,000–3,000,000	35%	235	192	Null Hypothesis	rejected
3,000,001–5,000,000	27%	177	204		
5,000,001–10,000,000	9%	62	112		
10,000,001–15,000,000	5%	35	20		
more than 15,000,000	2%	17	14		
Education Level					
Uneducated	7%	49	11	p- Value	2.6842E–60
Elementary School	21%	137	44	Null Hypothesis	rejected
High School	57%	379	373		
College/University & Postgraduate	15%	99	235		

Note: # (Bandung City Central Bureau of Statistics, 2018).