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FACTORS INFLUENCING THE ADOPTION OF ELECTRIC VEHICLE: THE CASE OF ELECTRIC MOTORCYCLE IN NORTHERN GHANA

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Abstract: Electric motorcycles are one way to reduce fossil fuel consumption and greenhouse gas emissions in the area of transportation. This survey utilizes both Logit and Probit frameworks to explore the likely factors influencing the adoption of the electric motorcycle in Northern Ghana. The outcomes from the two models are consistent with each other; they have similar signs for every factor except for a slight contrast in the magnitude of the coefficients. A survey was conducted in Northern Ghana to elicit information from motorcyclists through a questionnaire. The model takes into consideration motorcyclists' perceptions about technical specifications of electric motorcycles, such as charging times, the lifespan of the battery, the performance of the electric motorcycle, motorcyclists' perception of the price of the electric motorcycle, driving range and motorcyclists' ages, monthly income, among others. The results reveal that perception of the price of the electric motorcycle, government subsidies, performance of the electric motorcycle, high usage, and maximum distance has a substantial impact on motorcyclists' willingness to adopt electric motorcycles. The findings of this study will provide constructive advice to diverse stakeholders on the adoption of an electric motorcycle in Ghana.

Keywords: electric motorcycle, Logit model, Northern Ghana, Probit model, technology adoption.

1. Introduction

Automobile fuels such as gasoline and diesel produce toxic substances during combustion. Carbon dioxide and others-carbon monoxide, hydrocarbon, nitrogen oxide and, in the case of a diesel engine, exhaust gas-are discharged by cars. These pollutants cause global warming and are culprits of air pollution. According to the World Health Organization report, a total of 8.2 million deaths, 16% of global deaths, were credited to air pollution in 2012 (Prùss-Ustùn *et al*., 2016; Environmental Protection Agency, 2016).

The number of newly registered motorcycles in Ghana annually increased by 315% from the year 2008 to 2014, whereas the number of newly registered vehicles increased by 85% within the same period (Driver and Vehicle Licensing Authority, 2016).

Motorcycles play a vital role in Ghana's transportation system, particularly in Northern Ghana where they are the most

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popular means of transport for both humans and goods. Due to low cost, convenience, and ability to maneuver on congested roads, motorcycles are also becoming attractive for commercial passenger transport in major cities in Ghana although they are not legally permitted to be used as a public transportation (Akaateba *et al.*, 2015; Akaateba *et al.*, 2014). The prominence of motorcycles over vehicular mode of transport in the northern part of Ghana can be credited nonexistence of governmental intra-city public transport system and insufficient private ones, less motorable roads and the inability of the people to acquire private vehicles, a situation which is generally linked to the socio-economic characteristics of the people in the Northern Ghana (Dapilah *et al.*, 2017).

Electric vehicles are one way to reduce emissions in the transport sector because of their zero-level carbon emissions during use, low energy consumption, and relatively simple and mature technology (Wang *et al.*, 2018). They offer substantial economic and environmental benefits by substituting grid-based electricity for fossil fuels compared to the internal combustion engine vehicles. Also, they reduce greenhouse gas and other emissions, enhance energy security, and promote the use of renewable energy (Larson *et al.*, 2014; Egbue and Long, 2012).

Thus, this study aims to discover to what extent some issues are critical to explaining Ghanaian consumers' willingness to adopt an electric motorcycle by using a survey and the information obtained by 537 Ghanaian respondents. With this aim, the likelihood of consumers' stated willingness to consider the adoption of an electric motorcycle is explored using logistic regression. The study focuses on motorcyclists' perception about technical specifications of electric motorcycles, such as charging times, their perception of the price of an electric motorcycle, driving range, and motorcyclists' ages, among others. This study contributes to the literature on this topic in three ways: (i) it provides an empirical study about motorcyclists' decision-making to buy an electric motorcycle; (ii) it is the first attempt on this topic in Ghana; and (iii) it provides useful information to policymakers to discuss the critical elements related to the most appropriate industrial policy which help to promote the electric motorcycle. The rest of this paper is structured as follows. Chapter 2 is a brief review of the previous literature. Chapter 3 describes the data acquisition methods, and the research method and Chapter 4 summarizes the empirical results and discussion. Finally, Chapter 5 presents the conclusion of the study.

2. Literature Review

It is necessary to deeply investigate Ghanaian motorcyclists' perception of electric motorcycle and the influential factors that affect their intention to adopt the electric motorcycle to promote the sustainable transportation mode of an electric motorcycle in Ghana. Considering the innovative characteristics of an electric motorcycle, in the current research, we adopt and the theory of planned behavior (TPB) (Ajzen, 1991) as the basic theoretical model to understand the antecedents of consumers' willingness to adopt innovative technology. TPB is often considered as a common and robust model to address consumer adoption of the electric vehicle (Egbue and Long, 2012; Lane and Potter, 2007; Moons and de Pelsmacker, 2012; Wang *et al.*, 2016; Moons and De Pelsmacker, 2015). Several prior studies have adopted TPB to explore consumers' intention to adopt the electric vehicle and validated its usefulness and feasibility. For example, Wu *et al.* (2015) used the TPB to explore consumers' green purchase intentions of Taiwanese to buy electric motorcycle TPB is appropriate to explain the influential factors of consumer acceptance of sustainable transportation.

Electric vehicles provide a useful comparison basis for electric motorcycles because they have several of the same critical elements including a battery and electric motor-based powertrain and lower environmental impacts. As electric vehicles have been commercially available since the late 1990s, several studies used revealed preference data to investigate factors that influenced consumer uptake for those automobiles (Soto *et al.*, 2018; Wang *et al.*, 2016). To the best of our knowledge, the available literature provides a comprehensive assessment of adoption of electric motorcycles are Chiu and Tzeng (1999), Guerra (2017), Jones *et al*. (2013) and Wu *et al*. (2015). In the presence of relatively limited research on electric motorcycles, we have incorporated into our study variables that were found to be significant drivers of electric vehicle adoption in the literature.

The literature on consumer electric vehicles adoption has analyzed several factors affecting the adoption of electric vehicles. The focus of published studies has been on various aspects of adoption and non-adoption behavior. They have utilized different theories and studied different electric vehicles in different parts of the world (Rezvani *et al.*, 2015). Economic analysis of technology adoption has sought to explain adoption behavior about buyers' socio-demographic characteristics such as age, gender, and level of education, travel patterns, household attributes such as income and number of vehicles in the household (Weinert *et al.,* 2007a; Musti and Kockelman, 2011; Khan and Kockelman, 2012; Higgins *et al.*, 2012; Egbue and Long, 2012; Liu *et al.*, 2013; Axsen *et al.*, 2017).

Factors driving the market penetration of e-bikes in China include legislative support, technological improvement, price reduction, favorable transportation infrastructure, and favorable socio-economic and cultural conditions (Weinert *et al.*, 2007a; Weinert *et al.*, 2008; Weinert *et al.*, 2007b; Cherry and Cervero, 2007; Cherry, 2007).

Gallagher and Muehlegger (2011) studied the relative efficacy of state sales tax waivers, income tax credits, and non-tax incentives and found that the type of tax incentive offered is as imperative as the generosity of the incentive. Consequently, plug-in hybrid vehicle penetration is shown to be strongly dependent on permanent tax rebates, subsidies, and sales tax exemptions. Diamond (2009) examines the impact of government incentives policies designed to promote the adoption of hybrid-electric vehicles and found that the relationship between gasoline prices and hybrid adoption is strong, but a much feebler connection between incentive policies and hybrid adoption and incentives that provide payments upfront also appear to be the most effective.

Among the most significant barriers hindering the electric vehicles deployment, literature identifies cost competitiveness; whether regarding the total cost of ownership or purchase price (Morganti and Browne, 2018). Surveys show that many consumers express a willingness to pay a price premium for a more fuel-efficient vehicle (Lieven *et al.*, 2011; Eppstein *et al.*, 2011; Graham-Rowe *et al.*, 2012; Krupa *et al.*, 2014). Electric vehicle purchase prices, which are heavily dependent on battery costs, have been identified as being the most significant factors in electric vehicle adoption (Sierzchula *et al.*, 2014). Barth *et al.* (2016) find that the purchasing price is the most important factor related to the adoption of electric vehicles. Electric vehicles are usually more expensive to be bought. However, energy-saving technologies could be net-cost savers in the long run (Junquera *et al.*, 2016).

A key determinant of the adoption of the electric vehicle is an environmental concern because adoption of the electric vehicle is considered as an environmental protection action (Rezvani *et al.*, 2015). The issues of energy security, concerns about the environment, and the obtainability of alternative fuels, along with demographic characteristics, have significant effects on consumer purchase expectations for alternative-fuel vehicles (Li *et al.*, 2013). Krupa *et al.* (2014) find that those who are most concerned about climate change have a greater willingness to adopt electric vehicles. This study is consistent with other studies of Schuitema *et al.* (2013) and Yadav and Pathak (2016). Contrasts of electric bikes with cars and buses have reported that per kilometer traveled, even taking into account the longer lifetime of the automobiles, the electric bikes are very energy efficient and cleaner than cars on all metrics, except those using lead-acid batteries (Weinert *et al.,* 2007b; Cherry, 2007).

Charging time plays a critical role in the adoption process of electric vehicles. Many authors have analyzed charging time as one of the vital determinants of electric vehicle adoption (Hidrue *et al.*, 2011; Neubauer *et al.*, 2012; Beggs *et al.*, 1981; Bunch *et al.*, 1993; Chéron and Zins, 1997; Lieven *et al.*, 2011; Zhang *et al.*, 2011; Egbue and Long, 2012). Whereas most internal combustion engine vehicles can refuel in roughly 4 min, electric vehicles require approximate 30 min at a fast charging station and up to several (>10) h for charging from a 110 or 220 V outlet, dependent on battery size (Saxton, 2011). Lengthy charging times are considered a critical handicap to improve the market share of electric vehicles (Pilkington and Dyerson, 2002; Hård and Knie, 2001). An additional factor which influences consumer adoption of electric vehicles is the availability of charging stations (Yeh, 2007; Egbue and Long, 2012; Tran *et al.*, 2012; Neubauer and Wood, 2014).

In several studies, fuel (gasoline or diesel) prices have been identified as one of the most potent predictors of electric vehicle adoption (Diamond, 2009; Beresteanu and Li, 2011; Gallagher and Muehlegger, 2011). Related to fuel prices, although less commonly considered in analyses, is electricity costs. Those two factors combine to determine a majority of electric vehicle operating costs which in turn have an impact on adoption rates (Zubaryeva *et al.*, 2012; Dijk *et al.*, 2013).

The range is widely identified as a significant concern by potential electric vehicle buyers. The electric vehicle is powered solely by a rechargeable electric battery and can travel for up to 100 miles on one full charge (Pilkington and Dyerson, 2002; Hardman *et al.*, 2017; Van Haaren, 2012; Egbue and Long, 2012). Franke and Krems (2013) in their study treat range as a barrier to adoption and find that experience from driving all-electric vehicles produce the adaptation, which reduces the practical constraints of range. Consequently, range limitation can be considered as the adaption demand or the needed change or behavior relative to conventional internal combustion engine cars. Moreover, such changes in behavior make consumers resistant to the acceptance of battery electric vehicles (Caperello and Kurani, 2012; Lane and Potter, 2007). The current electric vehicle becomes less suitable when the daily trip distance of the user is more than 200 km (Krumm, 2012).

Rezvani *et al*. (2015) carried out a comprehensive overview of the drivers for and barriers against consumer adoption of plug-in electric vehicles, in addition to a review of the theoretical perspectives that have been applied for understanding consumer intentions and adoption behavior towards electric vehicles. They argued that various factors influence the adoption process. These factors are: Technical (e.g., instrumental, functional electric vehicle attributes); Contextual (e.g., policy, charging infrastructure), Cost (e.g., purchase price, fuel costs), individual and social factors (e.g., knowledge, perceived behavioral control, emotions, the symbolic meaning of the electric vehicle, subjective social norm) are all associated with battery electric vehicle adoption.

3. Materials and Methods

In this study, Tamale which doubles as the capital town of the Tamale Metropolitan Assembly and the regional capital of the Northern Region of Ghana was selected purposively for the research. The Tamale Metropolitan Assembly is the most populous district in the region, with a population of 371,351, representing 15 percent of the region's population. This massive concentration may be because Tamale is the capital of the region and is also centrally located. Commercial activities, job opportunities, as well as educational institutions in the metropolis are attracting people from other parts of the region. Tamale is selected because is one of the few cities in Ghana where the use of a motorcycle as a means of transport is widespread (Ackaah and Afukaar, 2010). Face-to-face interviews with questionnaires were used to solicit a response from the motorcycle owners. The questionnaire was divided into two parts where the first part is about demographic information, including will adopt electric motorcycle, gender, age, education background, monthly income, and household. The second part focuses on the attitude factors that may influence the adoption of an electric motorcycle, and this made up of statements that were used to explore consumer perception of barriers to electric motorcycle adoption. Eleven factors were chosen as possible barriers to electric motorcycle adoption from the review of the literature. Explanations of the potential barriers were provided to respondents to ensure that the respondents had a consistent understanding of the barriers. In this study, the Logit and Probit models and the associated odds ratios are estimated using Stata (version 14.0).

Table 1 below shows the variable with their definitions and a prior expectation. Among these variables is the "maximum education" of the respondent as described: 1=Primary school graduate, 2=Junior high school graduate, 3= Senior high school graduate, 4= Undergraduate degree, 5=Postgraduate degree and was modeled as a categorical variable. Another variable investigated in this study is "monthly income" and is defined as a categorical variable as well. This research aggregates monthly incomes into six categories: 1=less than ₵1,000, 2=₵1,000 to ₵2,000, 3=₵2,001 to ₵3,000, 4=₵3,001 to ₵4,000, 5=₵4,001 to₵5,000, 6=greater than ₵5,000. The Ghana Cedi and Euros ratio is 1 Ghana Cedi is equivalent to 0.18 Euro (XE Corporation, 2018).

Table 1

Variable with Their Definitions and a Prior Expectation

Variable	Definition	Expected Sign
Will adopt electric motorcycle	1 yes; 0 otherwise	+
Gender	1 if the respondent is a male; 0 otherwise	+/-
Age	Number of years	+/-
Maximum education	Level of formal education by the respondent	+/-
Monthly income	Monthly earnings of the respondent in Ghana Cedis	+/-
Household size	Total number of people in the household	+/-
Charging time of the battery	Time to recharge the battery of electric motorcycle in an hour	+/-
Lifespan of battery	The lifespan of the electric motorcycle battery in years	+/-
Riding pleasure	1 if the respondent likes riding; 0 otherwise	+
Operating cost	1 if the respondent thinks the operating cost of the electric motorcycle is less than that of the gasoline-powered motorcycle; 0 otherwise	+
Perception of the price	1 if the respondent considers the price of an electric motorcycle is higher than that of the gasoline-powered motorcycle; 0 otherwise	+
Environmental concern	1 if the respondent thinks the pollution by electric motorcycle is lower to a gasoline-powered motorcycle; 0 otherwise	+
Government subsidies	1 if the respondent will buy an electric motorcycle if there are subsidies on an electric motorcycle; 0 otherwise	+
Performance of electric motorcycle	1 if the respondent thinks the performance (acceleration, Speeding, and so forth.) is better than a gasoline-powered motorcycle; 0 otherwise	+
High usage to cover 200 Km	1 if the respondent uses the motorcycle with high frequency to cover 200 Km; 0 otherwise	-
Public charging of infrastructure	1 if the respondent will adopt electric motorcycle if public charging infrastructure is provided; 0 otherwise	+

A multistage sampling technique was used in selecting the motorcycle owners for the study. Motorcycle owners who have been riding a motorcycle continuously for the past five years were purposively selected. This technique was to avoid new motorcyclist, since they may not have adequate knowledge about the usage of the motorcycle. After purposive sampling, the simple random technique was used to select the required number of motorcycle owners for the interview. Six-hundred and twenty-seven motorcycle owners were interviewed for the study. The field survey started in June and ended in September 2017.

3.1. Statistical Model Specification

Methodologies used in this study follow the processes described by other researchers such as (Zhang *et al.*, 2011; Bunch *et al.*, 1993; Axsen and Kurani, 2011; Junquera *et al.*, 2016; Lin and Wu, 2018; Javid and Nejat, 2017; Soto *et al.*, 2018). The statistical modeling framework employed in this study to determine the possible factors influencing the adoption of the electric motorcycle was the Logit model. The choice of this type of model was influenced by the dichotomous nature of the response variable. This model is derived under the postulation that the error term ε is the Independent, Identically Distributed (IID) extreme value, which has a logistic distribution (Train, 2009). A Logit model will produce results like Probit regression, which uses a standard normal distribution for the error term. The choice of Probit versus Logit depends mostly on individual preferences. Since the dependent variable, or endogenous variable, is a 0 or 1 variable, we employ the Logit regression model. While the application of the Logit regression is the emphasis of this paper, the results of the Probit model are also provided for comparison. In this section, we describe mathematical formulations for the Logit regression model.

In this study, we use the multiple Logit models as described by (1) where $P(x)$ is the predicted probability of $y=1$ for a given value of x_k $(k=1, 2\ldots, P)$ (Hosmer *et al.*, 2013). The coefficients a and b_k $(k=1, 2\ldots, P)$ are determined according to a maximum likelihood approach, and it allows us to estimate the $P(x)$ (Hosmer *et al.*, 2013), Eq. (1) and Eq. (2).

$$\log \frac{P(x)}{1-P(x)} = a + \sum_{k=1}^{P} b_k x_k \qquad (1)$$

Solving for $P(x)$ gives the equation (2):

$$P(x) = \frac{1}{1+e^{-(a+\Sigma_k b_k x_k)}} \qquad (2)$$

For each data-point $(i=1, 2\ldots, n)$ we have a vector of features, x_i, and an observed class, y_i. The probability of that class was either $P(xi)$, if $y_i=1$, or $1-P(x_i)$, if $y_i=0$. The likelihood function, $L(a, b)$ is presented by Eq. (3), and the resulting log-likelihood function, $L'(a, b)$ is shown by Eq. (4). Placing Eq. (1) into Eq. (4) and differentiating the loglikelihood concerning the parameters will result in Eq. (5). The derivative in Eq. (5) is set to zero and solved to determine the coefficients a and b_k $(k=1, 2\ldots, P)$.

$$L(a,b) = \prod_{i=1}^{n} [P(x_i)^{yi}(1-P(x_i))^{1-y_i}] \qquad (3)$$

$$L'(a,b) = \sum_{i=1}^{n} [(y_i \log(P((x_i)) + (1-y_i)\log(1-P(x_i))] \qquad (4)$$

$$\frac{\partial L'}{\partial b_k} = \sum_{i=1}^{n} [y_i - P(x_i))x_{ik}] \qquad (5)$$

(where $k=1,2,3,\ldots,P$)

3.2. Marginal Effects

The inferences about the effect of a variable on the outcome are determined by its marginal effect. Marginal effects are estimates of the change in an outcome for a change in one independent variable, holding all other variables constant (Long and Freese, 2014).

Following the discussion in (Shaheed and Gkritza, 2014; Greene, 2012), the direct and cross-marginal effects are calculated following Eq. (6) and Eq. (7), respectively:

$$\frac{\partial P_{ij}}{\partial x_{ijk}} = \beta_{jk} P_{ij} (1 - P_{ij}) \quad (6)$$

$$\frac{\partial P_{ij}}{\partial x_{ijk}} = -\beta_{jk} P_{ij} P_{iq} \quad (7)$$

The direct marginal effect Eq. (6) represents the effect that a unit change in x_{ijk} has on the probability of outcome j (denoted by P_{ij}). The cross-marginal effect Eq. (7) shows the effect of a unit change in variable k of alternative j ($j \neq q$) on the probability (P_{iq}) of outcome q. For indicator variables, the marginal effects are computed as the difference in the estimated probabilities with the indicator variables changing from zero to one (rather than a unit change). The final marginal effect of a variable is calculated as the summation of the marginal effects for each class weighted by their posterior latent class probabilities.

4. Results and Discussion

Table 2 below shows the summary and the results of the variance inflation factor (VIF) test of the variables in this study. Based on the data sample, 74.9% are males; this means that more males ride a motorcycle than females. The mean age of the motorcyclists is approximately 40 years with 19 years been the minimum and 60 years the maximum. This result shows that that riding of motorcycle cut across the youth and the aged. On the maximum education of the respondents, it was revealed that an average educational level in the study is senior high school graduate. On average the households contain approximately three persons with one person been the minimum and seven persons the maximum.

The average charging time of battery 3.13 hours and the average lifespan of the battery is 3.02 years. This study employs the VIF to determine the multicollinearity problem in the model. Kutner *et al.* (2004) and Khatoon *et al.* (2013) suggested that multicollinearity is only severe when VIF is greater than 10. In this study, the reported VIFs are each less than 10, which indicate no multicollinearity among the explanatory variables as shown in Table 2 below.

Table 2

Summary and the Results of the VIF Test of the Variables

Variable	Mean	Std. Dev.	Min	Max	VIF	1/VIF
Gender	0.749	0.434	0	1	1.03	0.97
Age	39.695	10.718	19	60	1.14	0.88
Maximum education	2.732	1.232	1	5	1.14	0.88
Monthly income	2.721	1.456	1	6	1.15	0.87
Household size	2.417	1.521	1	7	1.04	0.96
Charging time of a battery	3.134	1.515	1	6	1.13	0.89
Lifespan of battery	3.017	1.356	1	7	1.04	0.96
Riding pleasure	0.963	0.190	0	1	1.11	0.90
Operating cost	0.449	0.498	0	1	1.20	0.83
Perception of the price	0.631	0.483	0	1	1.05	0.95
Environmental condition	0.490	0.500	0	1	1.08	0.93
Government subsidies	0.749	0.434	0	1	1.08	0.93
Performance of electric motorcycle	0.428	0.495	0	1	1.29	0.78
High usage to cover 200 Km	0.523	0.500	0	1	1.09	0.91
Public charging infrastructure	0.499	0.500	0	1	1.22	0.82
Maximum distance is less than 100 Km	0.446	0.498	0	1	1.45	0.69
Sample number	537					

The estimated coefficients, odds ratios, and marginal effects of the fitted Logit and Probit models of adoption of electric motorcycle are presented in Table III below. Although the coefficients are different, the odds ratios- the ratio of the probability of y=1 and the probability of y=0 are almost the same for Logit and Probit models (Long and Freese, 2014).

The results identify that perception of the price, government subsidies, the performance of the electric motorcycle, high usage to cover 200 Km, and maximum distance is less than 100 Km can significantly impact electric motorcycle adoption behavior. Based on both the Logit and Probit models, other variables in the model: gender, age, maximum education, monthly income, household size, charging time of battery, lifespan of battery, riding pleasure, operating cost, environmental condition, and public charging infrastructure are not statistically significant to explain the willingness to adopt electric motorcycle. The estimated coefficients of the independent variables do not show the dynamics among the outcomes. To deal with these questions, the exponentiated values of the estimated coefficient e^{β} referred to as the odds ratio can be used to explore how variables affect the choice of one outcome compared with another outcome (Long and Freese, 2014). Because the coefficient result only tells the direction of change and not the probability or magnitude of change (Long and Freese, 2014), marginal effects are analyzed and included in Table 3.

The relative overall fit indices for the models are shown in Table 3. The chi-squared values, p-values, correct classification and area under receiver operating characteristics (ROC) curves were considered to measure the goodness of fit of the models. These fit indices provide values that imply a good model fit to the data set. Only the parameters of the significant variables in the Logit model were used to simplify the presentation results and discussion.

The odds ratio value associated with the perception of the price is 0.260. Hence, when motorcyclist consider that the price of an electric motorcycle is higher than the price of a combustion engine motorcycle, the odds ratio of willingness to buy an electric motorcycle decreases by 3.846 (1/0.260) and, therefore, motorcyclists are 3.846 less times likely to buy an electric motorcycle, when other variables are controlled. According to marginal effects, setting all the other variables the same, the predicted probability of adopting electric motorcycle is decreased by 18.2% for a unit increase in the cost of the electric motorcycle.

The results of the fitted model indicate that the presence of government subsidies will be more likely to increase the odds ratio of willingness to adopt the electric motorcycle by almost 3.357 times compared to combustion engine motorcycle when other variables are constant. On the average, the government subsidies increased the predicted probability of adopting electric motorcycle by 16.3%.

Table 3
Estimated Parameters of Logit and Probit Models

Variable	Logit Coefficient	Probit Coefficient	Logit Odds Ratio	Probit Odds Ratio	Marginal effect (Logit)	Marginal effect (Probit)
Gender	0.078 (0.280)	0.044 (0.160)	1.081	1.045	0.010	0.010
Age	-0.020 (0011)	-0.011 (0.006)	0.980	0.989	-0.003	-0.003
Maximum education	-0.153 (0.103)	-0.085 (0.059)	0.858	0.918	-0.021	-0.020
Monthly income	0.140 (0.086)	0.080 (0.049)	1.150	1.084	0.019	0.019
Household size	0.070 (0.081)	0.048 (0.047)	1.072	1.049	0.009	0.011
Charging time of battery	0.125 (0.084)	0.072 (0.048)	1.133	1.074	0.017	0.017
Lifespan of battery	-0.032 (0.087)	-0.022 (0.050)	0.969	0.979	-0.004	-0.005
Riding pleasure	-0.505 (0.685)	-0.336 (0.384)	0.603	0.714	-0.068	-0.080
Operating cost	0.267 (0.260)	0.155 (0.149)	1.306	1.168	0.036	0.037
Perception of the price	-1.346 (0.268) **	-0.794 (0.152) **	0.260	0.452	-0.182	-0.188
Environmental condition	-0.001 (0.245)	-0.019 (0.140)	0.999	0.981	-0.000	-0.005
Government subsidies	1.211 (0.283) **	0.685 (0.162) **	3.357	1.984	0.163	0.162
Performance of electric motorcycle	1.986 (0.302) **	1.105 (0.161) **	7.283	3.019	0.268	0.262
High usage to cover 200 Km	-0.553 (0.256) *	-0.292 (0.143) *	0.575	0.747	-0.075	-0.069
Public charging infrastructure	-0.242 (0.256)	-0.148 (0.148)	0.785	0.863	-0.033	-0.035
Maximum distance is less than 100 Km	1.469 (0.292) **	0.857 (0.163) **	4.345	2.355	0.198	0.203
Constant	0.873 (0.994)	0.522 (0.567)				
Number of Observations:	537	537				
Log-likelihood at Zero:	-327.097	-327.097				
Log-likelihood at Convergence:	-224.934	-225.662				
LR Chi-Square Test:	204.325	202.869				
p-value:	0.000	0.000				
Pseudo R-squared:	0.312	0.310				
Akaike's Inf. Criterion	483.868	485.325				
Correct classifications	82.50%	82.12%				
The area under the ROC curve	0.8516	0.8518				

** >95% level of significance. ** >99% level of significance*

The odds ratio value associated with the performance of an electric motorcycle is 7.283. Hence, when motorcyclist consider that the performance of an electric motorcycle is better than that of a combustion engine motorcycle, the odds ratio of willingness to buy an electric motorcycle increases by 7.283 and, therefore, motorcyclists are 7.283 more times likely to adopt an electric motorcycle, holding all other variables constant. The most significant variable is the performance of the electric motorcycle, which results in a 26.8% increment in the probability of adopting an electric motorcycle.

The odds ratio of the high usage to cover 200 Km is 0.575. This result means that when the usage is high to cover 200 Km motorcyclist, the odds ratio of willingness to adopt an electric motorcycle decreases by 1.739 (1/0.575), so motorcyclists are 1.739 less time likely to adopt an electric motorcycle, holding all other variables constant. On the average, the high usage to cover 200 Km decreased the probability of adopting electric motorcycle by 7.5%.

The odds ratio value associated with the maximum distance is less than 100 Km is 4.345. Hence, when motorcyclists think that the distance which an electric motorcycle can go without recharging is less than 100 km, the odds ratio of willingness to adopt an electric motorcycle increases by 4.345 and, therefore, motorcyclists are 4.345 more times likely to buy an electric motorcycle, when other variables are constant. According to marginal effects, setting all the other variables the same, the predicted probability of adopting electric motorcycle is increased by 19.8%.

5. Conclusion

The primary aim of this study is to discover to what extent some factors are critical to explaining Ghanaian motorcyclists' willingness to adopt an electric motorcycle. A survey is used to obtain a motorcyclist profile's factors together with other barriers to adoption electric motorcycle by using multistage sampling techniques. When designing the survey questionnaire, previous literature and the realistic situation of Ghana were considered. The explanatory variables considered in this study are Gender, Age, Maximum education, Monthly income, Household size, Charging time of battery, Lifespan of battery, Riding pleasure, Operating cost, Perception of the price, Environmental concern, Government subsidies, Public charging of infrastructure, Performance of the electric motorcycle, High usage to cover 200 Km, and Maximum distance is less than 100 Km. Both Logit and Probit regression analyses were conducted to explain the willingness to adopt an electric motorcycle for 537 motorcyclists these variables. Both models gave the same signs/ direction of change; the differences in the coefficients are not much and could not alter the interpretation of the results.

The estimated models indicate that factors such as; perception of the price, government subsidies, the performance of the electric motorcycle, high usage to cover 200 Km, and maximum distance is less than 100 Km were found to have statistical significance in motorcyclists' adoption of an electric motorcycle. Other factors such as; gender, age, maximum education, monthly income, household size, charging time of the battery, the lifespan of the battery, riding pleasure, operating cost, environmental condition, and public charging infrastructure was not statistically significant. Based on these findings, both policymakers and electric motorcycle manufacturers might design specific strategies for inducing Ghanaian consumers to be potential electric motorcycle adopters.

References

Ackaah, W.; Afukaar, F.K. 2010. Prevalence of helmet use among motorcycle users in tamale metropolis, Ghana: An observational study, *Traffic Injury Prevention* 11(5): 522-525.

Ajzen, I. 1991. The theory of planned behavior, *Organizational Behavior and Human Decision Processes* 50(2): 179-211.

Akaateba, M.A.; Amoh-Gyimah, R.; Amponsah, O. 2015. Traffic safety violations in relation to drivers' educational attainment, training and experience in Kumasi, Ghana, *Safety Science* 75: 156-162.

Akaateba, M.A.; Amoh-Gyimah, R.; Yakubu, I. 2014. A cross-sectional observational study of helmet use among motorcyclists in Wa, Ghana, *Accident Analysis and Prevention* 64: 18-22.

Axsen, J.; Kurani, K.S. 2011. Interpersonal influence in the early plug-in hybrid market: Observing social interactions with an exploratory multi-method approach, *Transportation Research Part D: Transport and Environment* 16(2): 150-159.

Axsen, J.; Langman, B.; Goldberg, S. 2017. Confusion of innovations: Mainstream consumer perceptions and misperceptions of electric-drive vehicles and charging programs in Canada, *Energy Research and Social Science* 27: 163-173.

Barth, M.; Jugert, P.; Fritsche, I. 2016. Still underdetected - Social norms and collective efficacy predict the acceptance of electric vehicles in Germany, *Transportation Research Part F: Traffic Psychology and Behaviour* 37: 64-77.

Beggs, S.; Cardell, S.; Hausman, J. 1981. Assessing the potential demand for electric cars, *Journal of Econometrics* 17(1): 1-19.

Beresteanu, A.; Li, S. 2011. Gasoline Prices, Government Support, And The Demand For Hybrid Vehicles In The United States, *International Economic Review* 52(1): 161-182.

Bunch, D.S.; Bradley, M.; Golob, T.F.; Kitamura, R.; Occhiuzzo, G.P. 1993. Demand for clean-fuel vehicles in California: a discrete-choice stated preference pilot project, *Transportation Research Part A: Policy and Practice* 27(3): 237-253.

Caperello, N.D.; Kurani, K.S. 2012. Households' Stories of Their Encounters With a Plug-In Hybrid Electric Vehicle, *Environment and Behavior* 44(4): 493-508.

Chéron, E.; Zins, M. 1997. Electric vehicle purchasing intentions: The concern over battery charge duration, *Transportation Research Part A: Policy and Practice* 31(3): 235-243.

Cherry, C. 2007. Electric Bike Use in China and Their Impacts on the Environment, Safety, Mobility and Accessibility, *WORKING PAPER UCB-ITS-VWP-2007-3*, Berkeley.

Cherry, C.; Cervero, R. 2007. Use characteristics and mode choice behavior of electric bike users in China, *Transport Policy* 14(3): 247-257.

Chiu, Y.C.; Tzeng, G.H. 1999. The market acceptance of electric motorcycles in Taiwan experience through a stated preference analysis, *Transportation Research Part D: Transport and Environment* 4(2): 127-146.

Dapilah, F.; Guba, B.Y.; Owusu-Sekyere, E. 2017. Motorcyclist characteristics and traffic behaviour in urban Northern Ghana: Implications for road traffic accidents, *Journal of Transport and Health* 4: 237-245.

Diamond, D. 2009. The impact of government incentives for hybrid-electric vehicles: Evidence from US states, *Energy Policy* 37(3): 972-983.

Dijk, M.; Orsato, R.J.; Kemp, R. 2013. The emergence of an electric mobility trajectory, *Energy Policy* 52: 135-145.

Driver and Vehicle Licensing Authority. 2016. *Vehicle Registration and Licensing Statistics*, *National Report*, Accra.

Egbue, O.; Long, S. 2012. Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions, *Energy Policy* 48: 717-729.

Environmental Protection Agency 2016. Sources of Greenhouse Gas Emissions. Available from internet: <https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions>.

Eppstein, M.J.; Grover, D.K.; Marshall, J.S.; Rizzo, D.M. 2011. An agent-based model to study market penetration of plug-in hybrid electric vehicles, *Energy Policy* 39(6): 3789-3802.

Franke, T.; Krems, J.F. 2013. Interacting with limited mobility resources: Psychological range levels in electric vehicle use, *Transportation Research Part A: Policy and Practice* 48: 109-122.

Gallagher, K.S.; Muehlegger, E. 2011. Giving green to get green? Incentives and consumer adoption of hybrid vehicle technology, *Journal of Environmental Economics and Management* 61(1): 1-15.

Graham-Rowe, E.; Gardner, B.; Abraham, C.; Skippon, S.; Dittmar, H.; Hutchins, R.; Stannard, J. 2012. Mainstream consumers driving plug-in battery-electric and plug-in hybrid electric cars: A qualitative analysis of responses and evaluations, *Transportation Research Part A: Policy and Practice* 46(1): 140-153.

Greene, W.H. 2012. *Econometric Analysis*. The Prentice Hall Companies, Inc. USA. 1228p.

Guerra, E. 2017. Electric vehicles, air pollution, and the motorcycle city: A stated preference survey of consumers' willingness to adopt electric motorcycles in Solo, Indonesia, *Transportation Research Part D: Transport and Environment* (June): 1-13.

Hård, M.; Knie, A. 2001. The Cultural Dimension of Technology Management: Lessons from the History of the Automobile, *Technology Analysis & Strategic Management* 13(1): 91–103.

Hardman, S.; Shiu, E.; Steinberger-Wilckens, R.; Turrentine, T. 2017. Barriers to the adoption of fuel cell vehicles: A qualitative investigation into early adopters attitudes, *Transportation Research Part A: Policy and Practice*, 95: 166-182.

Hidrue, M.K.; Parsons, G.R.; Kempton, W.; Gardner, M.P. 2011. Willingness to pay for electric vehicles and their attributes, *Resource and Energy Economics* 33(3): 686-705.

Higgins, A.; Paevere, P.; Gardner, J.; Quezada, G. 2012.. Combining choice modelling and multi-criteria analysis for technology diffusion: An application to the uptake of electric vehicles, *Technological Forecasting and Social Change* 79(8): 1399-1412.

Hosmer, D.W.; Lemeshow, S.; Sturdivant, R.X. 2013. Applied Logistic Regression. The John Wiley & Sons, Inc. USA. 518p.

Javid, R.J.; Nejat, A. 2017. A comprehensive model of regional electric vehicle adoption and penetration, *Transport Policy* 54: 30-42.

Jones, L.R.; Cherry, C.R.; Vu, T.A.; Nguyen, Q.N. 2013.. The effect of incentives and technology on the adoption of electric motorcycles: A stated choice experiment in Vietnam, *Transportation Research Part A: Policy and Practice* 57: 1-11.

Junquera, B.; Moreno, B.; Álvarez, R. 2016. Analyzing consumer attitudes towards electric vehicle purchasing intentions in Spain: Technological limitations and vehicle confidence, *Technological Forecasting and Social Change* 109: 6-14.

Khan, M.; Kockelman, K.M. 2012. Predicting the market potential of plug-in electric vehicles using multiday GPS data, *Energy Policy* 46: 225-233.

Khatoon, M.; Tiwari, G.; Chatterjee, N. 2013. Impact of grade separator on pedestrian risk taking behavior, *Accident Analysis and Prevention* 50: 861-870.

Krumm, J. 2012. How People Use Their Vehicles: Statistics from the 2009 National Household Travel Survey. Available from Internet: <https://www.sae.org/publications/technical-papers/content/2012-01-0489/>.

Krupa, J.S.; Rizzo, D.M.; Eppstein, M.J.; Lanute, D.B.; Gaalema, D.E.; Lakkaraju, K.; Warrender, C.E., 2014. Analysis of a consumer survey on plug-in hybrid electric vehicles, *Transportation Research Part A: Policy and Practice* 64: 14-31.

Kutner, M. H.; Nachtsheim, C. J.; Neter, J. 2004. Applied Linear Regression Models. The McGraw-Hill Companies, Inc. USA. 700p

Lane, B.; Potter, S. 2007. The adoption of cleaner vehicles in the UK: exploring the consumer attitude-action gap, *Journal of Cleaner Production* 15: 1085-1092.

Larson, P.D.; Viáfara, J.; Parsons, R.V.; Elias, A. 2014. Consumer attitudes about electric cars: Pricing analysis and policy implications, *Transportation Research Part A: Policy and Practice* 69: 299-314.

Li, X.; Clark, C.D.; Jensen, K.L.; Yen, S.T.; English, B.C. 2013. Consumer purchase intentions for flexible-fuel and hybrid-electric vehicles, *Transportation Research Part D: Transport and Environment* 18(1): 9-15.

Lieven, T.; Mühlmeier, S.; Henkel, S.; Waller, J.F. 2011. Who will buy electric cars? An empirical study in Germany, *Transportation Research Part D: Transport and Environment* 16(3): 236-243.

Lin, B.; Wu, W. 2018. Why people want to buy electric vehicle: An empirical study in first-tier cities of China, *Energy Policy* 112: 233-241.

Liu, W.; Wang, C.; Mol, A.P.J. 2013. Rural public acceptance of renewable energy deployment: The case of Shandong in China, *Applied Energy* 102: 1187-1196.

Long, J.S.; Freese, J. 2014. *Regression Models for Categorical Dependent Variables Using* Stata. The StataCorp LP. USA. 618p.

Moons, I.; de Pelsmacker, P. 2012. Emotions as determinants of electric car usage intention, *Journal of Marketing Management* 28: 195-237.

Moons, I.; De Pelsmacker, P. 2015. An extended decomposed theory of planned behaviour to predict the usage intention of the electric car: A multi-group comparison, *Sustainability (Switzerland)* 7(5): 6212-6245.

Morganti, E.; Browne, M. 2018. Technical and operational obstacles to the adoption of electric vans in France and the UK: An operator perspective, *Transport Policy* 63: 90-97.

Musti, S.; Kockelman, K.M. 2011. Evolution of the household vehicle fleet: Anticipating fleet composition, PHEV adoption and GHG emissions in Austin, Texas, *Transportation Research Part A: Policy and Practice* 45(8): 707-720.

Neubauer, J.; Brooker, A.; Wood, E. 2012. Sensitivity of battery electric vehicle economics to drive patterns, vehicle range, and charge strategies, *Journal of Power Sources* 209: 269-277.

Neubauer, J.; Wood, E. 2014. The impact of range anxiety and home, workplace, and public charging infrastructure on simulated battery electric vehicle lifetime utility, *Journal of Power Sources* 257: 12-20.

Pilkington, A.; Dyerson, R. 2002. Extending simultaneous engineering: electric vehicle supply chains and new product development, *International Journal of Technology Management* 23(1-3): 74-88.

Prüss-Üstün, A.; Wolf, J.; Corvalán, C.; Bos, R.; Neira, M. 2016. Preventing disease through healthy environments: a global assessment of the burden of disease from environmental risks. Available from Internet: <http://apps.who.int/iris/bitstream/handle/10665/204585/9789241565196_eng.pdf >.

Rezvani, Z.; Jansson, J., Bodin, J. 2015. Advances in consumer electric vehicle adoption research: A review and research agenda, *Transportation Research Part D: Transport and Environment* 34: 122-136.

Saxton, T. 2011. Understanding Electric Vehicle Charging. Available from internet: <http://www.pluginamerica.org/drivers-seat/understanding-electric-vehicle-charging>.

Schuitema, G.; Anable, J.; Skippon, S.; Kinnear, N.; 2013. T. The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles, *Transportation Research Part A: Policy and Practice* 48: 39-49.

Shaheed, M.S.; Gkritza, K. 2014. A latent class analysis of single-vehicle motorcycle crash severity outcomes, *Analytic Methods in Accident Research* 2: 30-38.

Sierzchula, W.; Bakker, S.; Maat, K.; Van Wee, B. 2014. The influence of financial incentives and other socio-economic factors on electric vehicle adoption, *Energy Policy* 68: 183-194.

Soto, J.J.; Cantillo, V.; Arellana, J. 2018. Incentivizing alternative fuel vehicles: the influence of transport policies, attitudes and perceptions, *Transportation* 1–33.

Train, K.E. 2009. *Discrete Choice Methods with Simulation*. The Cambridge University Press. USA. 400p.

Tran, M.; Banister, D.; Bishop, J.D.; McCulloch, M.D. 2012. Realizing the electric-vehicle revolution, *Nature Climate Change* 2(5): 328-333.

Van Haaren, R. 2012. Assessment of electric cars' range requirements and usage patterns based on driving behavior recorded in the National Household Travel Survey of 2009. Available from Internet: <http://legacy.veva.ca/papers/HowFarWeDrive_v1.2.pdf>.

Wang, E.; Guo, Q.; Shen, J. 2018. Examining Shanghai Consumer Preferences for Electric Vehicles and Their Attributes, *Sustainability* 10(6): 1-16.

Wang, S.; Fan, J.; Zhao, D.; Yang, S.; Fu, Y., 2016. Predicting consumers' intention to adopt hybrid electric vehicles: using an extended version of the theory of planned behavior model, *Transportation* 43(1): 123-143.

Weinert, J.; Ma, C.; Yang, X.; Cherry, C. 2007a. Electric Two-Wheelers in China: Effect on Travel Behavior, Mode Shift, and User Safety Perceptions in a Medium-Sized City, *Transportation Research Record: Journal of the Transportation Research Board* 2038: 62-68.

Weinert, J.; Ogden, J.; Sperling, D.; Burke, A. 2008. The future of electric two-wheelers and electric vehicles in China, *Energy Policy* 36(7): 2544-2555.

Weinert, J.; Ma, C.; Cherry, C. 2007b. The transition to electric bikes in China: History and key reasons for rapid growth, *Transportation* 34(3): 301-318.

Wu, J.H.; Wu, C.W.; Lee, C.T.; Lee, H.J. 2015. Green purchase intentions: An exploratory study of the Taiwanese electric motorcycle market, *Journal of Business Research* 68(4): 829-833.

XE Corporation. 2018. XE: Convert EUR/GHS. Euro Member Countries to Ghana Cedi. Available from Internet: <https://www.xe.com/currencyconverter/convert/?From=EUR&To=GHS>.

Yadav, R.; Pathak, G.S. 2016. Young consumers' intention towards buying green products in a developing nation: Extending the theory of planned behavior, *Journal of Cleaner Production* 135: 732-739.

Yeh, S. 2007. An empirical analysis on the adoption of alternative fuel vehicles: The case of natural gas vehicles, *Energy Policy* 35(11): 5865-5875.

Zhang, Y.; Yu, Y.; Zou, B. 2011. Analyzing public awareness and acceptance of alternative fuel vehicles in China: The case of EV, *Energy Policy* 39(11): 7015-7024.

Zubaryeva, A. et al. 2012. Assessing factors for the identification of potential lead markets for electrified vehicles in Europe: Expert opinion elicitation, *Technological Forecasting and Social Change* 79(9): 1622-1637.