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Examining the two-dimensional perceived marketplace influence and the role of financial incentives by SEM and ANN

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Abstract

In recent years, research on sustainable consumption has been particularly relevant, highlighting the importance of the collective over the individual to reduce pollution. This study focuses on the study of the perceived marketplace influence (PMI) concept in its organizational and consumer dimensions, together with the financial incentives that exist in the adoption of electric cars and their effect on green customer engagement. A sample of 382 potential buyers of electric vehicles was obtained. A new hybrid analytical approach was taken structural equation modelling and artificial neural network. The research found the most significant variables affecting purchase intention were financial incentives, followed by PMI Organization and finally PMI Consumer. The results of artificial neural network analysis confirmed all the findings of the structural equation modelling, although the importance of each PMI dimension is different for each technique used. The conclusions point to new business opportunities that can be exploited by companies selling this green technology.

KEYWORDS
electric vehicle, financial incentives, green customer engagement, perceived marketplace influence

1 | INTRODUCTION

Economic and social expansion, together with the exploitation of natural resources, has led to environmental degradation due to the unsustainable practices (Sreen et al., 2018). The main responsible for the current situation of environmental deterioration and the existing high pollution is attributed to human beings and their consumption and exploitation patterns (Park & Lin, 2020). Consequently, in recent years, an increasing number of companies are focusing their strategy on social responsibility and sustainable marketing. Organizations aim to provide long-term social value and well-being with the goal of preserving natural resources for future generations. The success of sustainable initiatives of firms depends on the adoption by consumers, so they play the main role by modifying their purchasing behaviour and, with them, the entire business fabric. Nowadays, individuals are showing an increased interest in adopting environmentally friendly products (Grau-Berlanga et al., 2022), however, such behaviour has not yet become real and widespread (Joshi & Rahman, 2019). Therefore, identifying and analysing the factors that motivate consumers to adopt less polluting and/or environmentally friendly products is fundamental for the general welfare of society and for organizations and regulators that aim to establish sustainable market models.

In line with the Paris Agreement, the European Union aims to reduce CO_2 emissions in all sectors of the economy (European Commission, COM, 2019a). To achieve this, the transport sector is fundamental, specifically, the electric vehicle is the central element to reduce emissions of polluting gases. According to the III Sustainable Mobility Observatory (2022), sustainable mobility has a cross-cutting impact on the achievement of many of the 17 Sustainable Development Goals. Transport is responsible for a quarter of greenhouse gas emissions, mainly from gasoline, diesel, and kerosene internal combustion vehicles. As a result, the adoption of electric vehicles is helping to control climate change, which has a direct effect on cities and people's health. Similarly, for the European Green Deal (COM, 2019b), which aims to achieve climate neutrality in Europe by 2050, electric mobility is one of the essential keys to the decarbonization process. In addition, the European Commission has approved the new program to save polluting emissions Fit for 55 (COM, 2021), in which the main proposal is to bring forward to 2035 the ban on the sale of internal combustion cars that is, diesel, gasoline and hybrids. It even contemplates the establishment of a new CO_2 tax on vehicles, initially affecting only companies and not private individuals.

In 2022, more than 10 million electric vehicles will be sold worldwide. According to the latest edition of the Global Electric Vehicle Outlook (IEA, 2023), it is estimated that sales will increase by 35% in 2023 to reach 14 million, thus reaching a share of close to a fifth of the automotive market. In this way, the participation will increase to 18%, compared to the 4% registered in 2020 and 14% in 2022. Most of the sales of electric cars are mainly concentrated in three markets: China, which accounted for 60% of the global sales last year and where more than half of the operational electric vehicles circulate globally; Europe and the United States, which in 2022 experienced sales growth of 15% and 55%, respectively.

Taking data from 14 world markets as a reference, the annual study by Ernst and Young (2022) on how prepared countries are for the adoption of electric cars, indicates that the most prepared country is China, in second place, Norway and after we have Sweden. China has the best offer in terms of variety, demand is predictable, and it concentrates 41% of the world's fast and ultra-fast chargers. On the other hand, the great advance in Norway is the result of years of policies that favour the buyer at the tax level, use (tolls, bus lanes, parking fees…) and with a compelling objective of eliminating internal combustion. In the case of Sweden, the reasons are similar, in addition to the fact that in both countries the per capita income is high. After these countries would be Germany and the United Kingdom. On the other hand, the US draws attention for its poor demand, which is explained by a weak regulatory framework to favour the product, the distances to travel can be enormous and the recharging points are insufficient. As well as the average price of an electric vehicle being higher than the average.

Although, according to the forecasts of the III Sustainable Mobility Observatory (2022), the purchase of electric vehicles needs to be extended to meet the planned objectives. According to the InfluenceMap study (2022), the major automotive companies have publicly declared their support for the Paris Agreement, however, only Tesla and Mercedes-Benz are really committed to a policy in line with the objectives of this treaty against climate change. Only two companies out of the 12 analysed will transition to electric vehicles fast enough to meet the goal of limiting global warming to 1.5°C. This shows that large electric vehicles manufacturers are not prepared for the transition, which makes it difficult to implement measures and policies favourable to reducing climate change. Consequently, it is necessary to increase the production and sale of electric vehicles, for which it is important to continue research in this area of study from the consumer's perspective. For all these reasons, to analyse the impact of the factors mentioned above, the research chooses the electric vehicle as a sustainable product and the perceived marketplace influence (PMI) concept. PMI is defined as "the belief that one's efforts in the marketplace can influence the behaviour of other consumers and organizations and thus serves as a motivation for one's own behaviour" (Leary et al., 2014). This concept was recently adopted in scientific research (Leary et al., 2014) and the measurement scale was developed by Leary et al. (2017). Due to its novelty, its application is currently very limited. Previous studies have shown that there is a gap between attitude and behaviour (Geng et al., 2017), so the research analyzes factors of different nature, on the one hand, Perceived Marketplace Influence (PMI) which implies a reward or satisfaction at an intrinsic level and, on the other hand, financial incentives, which implies an external reward in exchange for carrying out a sustainable purchasing behaviour. Although electric vehicles are more environmentally friendly products than internal combustion vehicles, the initial cost makes them less accessible, which is why governments encourage the purchase with aid such as registration tax benefits, registration tax benefits. property, business tax benefits and VAT benefits, in addition to other financial, local and infrastructure benefits. As mentioned above, Norway has been the country that has helped the purchase the most by being exempt from paying registration tax and VAT, as well as paying the minimum in circulation tax. It is now the country with the highest number of plug-in vehicles per capita in the world, although it has already begun to reduce this aid. France offers its buyers up to €11,000 and there are also exemptions on taxes. For its part, Iceland eliminated the payment of all taxes related to the purchase or use of electric cars and offers aid for charging facilities. In the case of the Spanish market, the latest plan linked to electric mobility dedicated a total of €1,200,000,000 aimed at the purchase of vehicles and the implementation of charging infrastructure (Real Decreto 266, 2021). In short, financial incentives are part of a very important driving factor in the purchase of electric vehicles.

Therefore, to investigate how the individual and business perspective influences individual purchasing behaviour, the study focuses on the PMI concept. PMI is a two-dimensional construct and there is great uncertainty about how each dimension influences behaviour. Prior research has analysed the construct (Joshi et al., 2021; Schneider & Leonard, 2022) or independently (Leary et al., 2019). While the literature supports the adequacy of PMI in predicting sustainable consumption, different contexts may show unique results in the perception of influence on other consumers or organizations. According to Leary et al. (2017), although the scales are correlated, their effects may differ by context. Consequently, this research further explores and examines PMI's two dimensions of purchasing behaviour for a green product such as electric vehicles. In addition, it confronts PMI with financial incentives. That is, intrinsic (PMI) and extrinsic (financial incentives) motivations. Two methodological techniques are applied: structural equation modelling (SEM) and artificial neural network (ANN) to add more value and rigour in the analysis of the two-dimensionality of the PMI concept.

Research contributes to the literature on the purchase intention of EVs' in several ways. First the literature on EVs' has mainly focused on large economies (Asif et al., 2021; Higueras-Castillo, Molinillo, et al., 2020). While studies on emerging economies is on the rise (Habich-Sobiegalla et al., 2018; Singh et al., 2023), research on Small Island Developing States remains scarce. Second, from a theoretical perspective, research applies PMI for the first to gauge the intention of consumers to buy EVs. Furthermore, the research proves the dimensional role of the construct. Third, we contribute to the antecedents of EVs purchase intention by highlighting that financial incentives continue to play the most significant role in the EV adoption.

This paper is structured as follows; next the literature review is carried out together with the justification of the research hypotheses. Further on, the data collection, measurement scale used, and the methodology applied are explained. The results are analysed to finally explain the theoretical conclusions and make appropriate practical recommendations.

2 | LITERATURE REVIEW

Research on sustainable consumption (Cho et al., 2013), environmental concern and even some studies on electric vehicle adoption have studied the role of perceived consumer effectiveness (PCE). For example, He and Zhan (2018) show that PCE is a positive predictor of personal norms and intention to adopt electric vehicles; Higueras-Castillo et al. (2019) point out PCE moderates consumer attitudes; Asadi et al. (2021) confirm that PCE directly impacts the intention to use electric vehicles. PCE refers to the belief that an individual's efforts can make a difference in solving a problem (Ellen et al., 1991), in this case environmental. In recent years, however, the term of perceived marketplace influence (PMI, Leary et al., 2014) has emerged. Although certain similarities with the PCE concept exists, they are different.

As mentioned earlier, PMI is defined as "the belief that one's efforts in the marketplace can influence the behaviour of other consumers and organizations and thus serve as a motivation for one's own behaviour". Specifically, when a person perceives that his or her actions influence the behaviour of others, his or her own behaviour is affected by this belief. Therefore, if people believe that their decision to adopt a sustainable behaviour (i.e. buying an electric vehicle) bias the conduct of other customers and companies, their adoption intention will be higher. While, PCE focuses on whether a person feels that his/her actions makes a difference to issues, PMI involves an individual's belief his/her behaviour influences the actions of other people and organizations. Therefore, it offers a more complete view of how customers' values and beliefs relate to market activity. Similarly, PMI is a broader concept than self-efficacy (Bandura, 1997) and collective efficacy (Bandura, 2000). However, this concept has been barely applied in the field of sustainable consumption and there are no studies explaining its validity in the specific context of the adoption of electric vehicles. The primary findings in relation to PMI are summarized below.

In general, PMI can constitute an enhancer of sustainable consumption as the influence a person perceives he or she has on others can pose a reason to perform a behaviour (Leary et al., 2014). If a person believes that his or her behaviour motivates others towards the same goal, he or she is more likely to perform that action as it involves a larger group of customers (Farah & Newman, 2010). Along these lines, Joshi and Rahman (2017, 2019) found that participants in their study are convinced that individual effort can influence the behaviour of other market actors, thus observing that respondents with high PMI are more positive towards sustainable purchasing behaviour.

Later, Leary et al. (2017) developed a 10-item scale for PMI and displayed its predictive and incremental validity in explaining environmental behaviour. Their study demonstrates that PMI acts as a mediating belief between environmental concern and behaviour. The measurement instrument differentiates between two dimensions of PMI: PMI Consumer and PMI Organization, which may differ in their impacts on behaviour, so they recommend investigating such a concept to other situation-specific beliefs (Leary et al., 2017). On the one hand, In the pro-environmental coffee shop context, Kim and Yun (2019) demonstrate the mediating effect of PMI on pro-environmental behavioural intentions and that switching cost moderates this relationship. On the other hand, Leary et al. (2019) study the influence of PMI on ethical marketplace behaviour. They show PMI is related to positive word of mouth and the purchase intention of ethical products. Moreover, the research point out the differences between the two dimensions of PMI based on the product type. Specifically, PMI Consumer is related to intention to buy products with hedonic qualities, while PMI Organization is associated with the intention to use utilitarian products. In addition, PMI is relevant in the context of mask wearing during the COVID-19 pandemic. Schneider and Leonard (2022) test whether PMI reduces the relationship between mask-wearing anxiety and mask-wearing. Thus, if individuals believe that wearing a mask will motivate others to wear it as well, that belief will motivate them to wear it. Finally, the study by Joshi et al. (2021) analyzes the impact of PMI, economic and emotional values on the attitude towards purchasing green products. Their study shows that they all have a significant and positive influence, however, the impact of PMI is lower compared to economic value and emotional value.

In view of the literature review, the current research proposes that PMI Consumer, PMI Organization, and financial incentives act as causal factors that influence the intention to buy an electric car, a behaviour generally perceived to be sustainable. The purchase of an electric car involves a high economic cost, and, in its consumption, we are seen by others. In addition, a car conveys a social and status image. Therefore, analysing these factors together is justified. Likewise, it would be interesting to know the strength of the impact of each of these factors. As a result, the following research hypotheses are proposed:

H1. *Perceived marketplace influence consumer* positively influences the intention to purchase an electric car.

H2. *Perceived marketplace influence organization* positively influences the intention to purchase an electric car.

Earlier studies have verified the positive and direct effect of financial incentives on electric vehicle adoption (Gong et al., 2020; Wang et al., 2018). Specifically, Münzel et al. (2019) have analysed data from 32 European countries from 2010 to 2017. They pointed out financial incentives lead to an increase in the sales share about 5%–7% per 1000€. However, there is conflicting data on the effectiveness of public incentives (Coffman et al., 2017). Therefore, some studies claim that financial incentives do not have a significant effect on electric vehicle adoption (Clinton & Steinberg, 2019) or there are others that are more important (Higueras-Castillo et al., 2021). While a few recommendations are given for their proper implementation. For example, apply them at the time of purchase, not after; VAT and purchase tax exemptions are very effective; incentives should not be available for high-end vehicles; incentives should be further promoted in vehicles with high electric autonomy (Hardman et al., 2017). For these reasons, a direct and positive relationship between financial incentives and electric vehicle purchase is posited:

H3. Financial incentives *positively influence the intention to purchase an electric car.*

In recent years, both academic research and business practice have considered customer engagement a key and determining factor in their long-term strategies (Pansari & Kumar, 2017). In this sense there is an obvious relationship between engagement and purchase from a transactional lens (Pansari & Kumar, 2017). Customer engagement behaviour is defined as a manifestation of behaviour towards the focal firm, beyond purchase, resulting from motivational drivers (Barari et al., 2021; van Doorn et al., 2010). Definition of customer engagement behaviour indicates attitudinal commitment as a driver of behavioural engagement (van Doorn et al., 2010), although the relationship between them has not been sufficiently studied. Based on these reasoning, the positive influence between purchase intention and Green Customer engagement is proposed from the approaches of Hollebeek et al. (2014), who precisely define engagement as the positive balance that the consumer makes of the brand in relation to affective, cognitive and behavioural factors during the consumer-brand interaction. On the other hand, Saks (2006) defines engagement as a distinctive factor composed of components related to cognition, emotion and behaviour that are linked to the individual's role performance. This concept is being adopted in the field of green economy and its environmental consequences. Specifically, green customer engagement refers to commitment to a product because of its environmental value. In this case, it refers to the commitment acquired with the electric vehicle thanks to the environmental benefits of its use.

In short, there are several authors in different scientific areas who propose that the adoption of a certain technology helps companies to achieve customer engagement through social interaction, obtaining rewards and behavioural change (Abou-Shouk & Soliman, 2021; Eisingerich et al., 2019) consequently favouring customer engagement (Glavee-Geo et al., 2020; Marcucci et al., 2018). Consequently, the following research hypothesis is proposed:

H4. *Intention to adopt an electric car* positively influences green customer engagement.

Figure 1 shows graphically the proposed behavioural model.

3 | METHODS

3.1 | Data collection

The population of Mauritius comprises 1.2 million inhabitants (Statistics Mauritius, 2022). The population for this study encompasses all people holding a valid driving licence. As the list of people holding a valid driving licence was not available, we used a purposive sampling technique to gather data from respondents via a Google form through social media. Therefore, it was distributed using the snowball method through convenience sampling. The final sample was 382 participants from Mauritius. The data were collected between May 2021 and March 2022. The sample represents adequately the population with a roughly equal representation of males and females and a proper balance of high (11%), medium (32%) and low income (56%), 55% had less than 40 years old and 57% had less than Rs. 50,000. In addition, 92% of respondents owned a vehicle, showing the respondents already have the experience of owning a car and can decide to purchase an electric car (see Table 1).

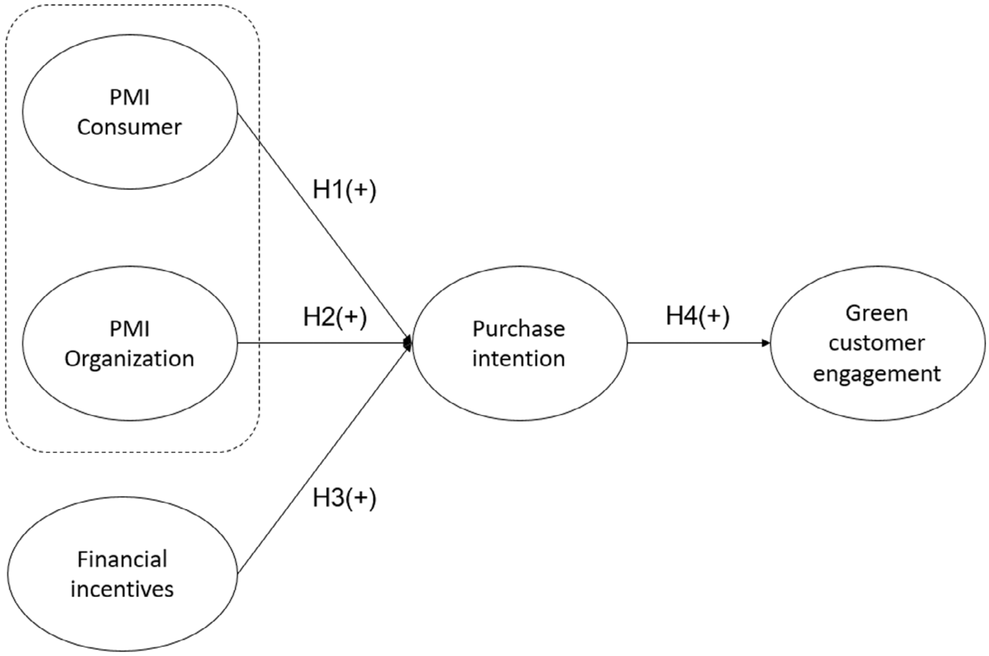

FIGURE 1 Proposed behavioural model.

TABLE 1 Sample profile.

Measure	N	%		N	%
Gender			*Monthly income*		
Male	218	57.1	<Rs. 50,000	217	56.8
Female	156	40.8	Rs. 50,000 but less than Rs. 80,000	91	23.8
Prefer not to say	8	2.1	Rs. 80,000 but less than 110,000	31	8.1
Age			Rs. 110,000 but less than Rs. 140,000	16	4.2
<30 years old	108	28.3	>Rs. 140,000	27	7.1
30 but less than 40	103	27.0	*Type of vehicle*		
40 but less than 50	118	30.8	Fossil fuel vehicle	203	53.1
50 but less than 60	40	10.5	Plug-in hybrid electric vehicle	6	1.6
Above 60 years old	13	3.4	Hybrid electric vehicle	129	33.8
Education			Electric vehicle	15	3.9
Secondary	31	8.1	I do not own a vehicle	29	7.6
Professional	28	7.3			
Diploma	41	10.7			
Bachelor degree	127	33.2			
Master degree	125	32.7			
Doctorate	26	6.8			
Other	4	1			

3.2 | Measurement scales

All measurement scales applied under Likert-type 1–7 points. Participants had to mark their degree of agreement with each statement (see Table 2). These scales are validated in previous studies and were adapted to the context of the study area. First, PMI scale was adapted from Leary et al. (2017), financial incentives was adapted from Wang et al. (2017), purchase intention was adapted from Sahin et al. (2012) and green customer engagement from Pansari and Kumar (2017) and Ullah et al. (2021).

Data were analysed using SmartPLS 4 software using the partial least squares (PLS) method in a structural equation model (Henseler et al., 2014). The two most important reasons for using the PLS technique in this research are the few restrictions on the normality of the data (Chin et al., 2003) and the possibility of evaluating the proposed model based on the explained variance, assessing the characteristics of the model. measurement model. For these reasons, the present investigation addressed this methodology. This is a research study in an emerging field that presents a lack of normality in the distribution of the sample collected.

4 | RESULTS

As a first step in data analysis, the multivariate assumptions (i.e. normality, linearity, multicollinearity, and homoscedasticity) were tested (Leong et al., 2019). Normality was assessed through One sample Kolmogorov–Smirnov (KS) test (Hasan et al., 2022). The results, presented in Table 2, illustrate that all p-values were equal to zero that is, smaller than 0.05, which further implies that data distribution in the research model is not-normal (Leong et al., 2019). Hence, PLS-SEM was used in this study because it is robust against non-normal distribution compared to the covariance-based SEM (Leong, Hew, Ooi, & Dwivedi, 2020).

To investigate the linearity of the relationships between the dependent variable and its predictors, ANOVA test was performed (Lee et al., 2020). The test results, presented in the Table 3, indicate the existence of significant non-linearity in the relationship between FI and PI.

Multicollinearity was assessed based on tolerance and variance inflation factor (VIF) values (Leong et al., 2019) and the test results are presented in Table 4. Since the tolerances are all above 0.1 and the VIF factors are all below the recommended cut-off value of 5 (Talwar et al., 2022), there is no issue of multicollinearity in the research model.

Finally, homoscedasticity was assessed based on the dispersion of regression standardized residuals (Hasan et al., 2022). Since the residuals were scattered evenly along a straight line, indicating that the variance is homogenous and homoscedasticity is achieved (Leong, Hew, Ooi, & Dwivedi, 2020).

Next, the common method bias (CMB) was assessed. Harman's single factor is used for it, via all items are loaded into a single common factor. CMB has no impact on the data as long as the total variance for a single factor is less than 50%. The test indicate they can explain 46% of the variance. Thus, it is concluded there is no CMB.

Then, the measurement model was analysed. The data was analysed using reliability, convergent analysis and discriminant analysis. The following indicators and the recommended limit in each case are taken into account for the assessment. Cronbach's α (acceptable value $= 0.7$, Cronbach, 1951), composite reliability (CR; acceptable value $= 0.7$) and average variance extracted (AVE; acceptable value $= 0.5$; Fornell &

TABLE 2 One-sample Kolmogorov–Smirnov test for normal distribution.

		Normal parameters[a,b]		Most extreme differences				
	N	Mean	SD	Absolute	Positive	Negative	Kolmogorov–Smirnov *Z*	Asymp. sig. (2-tailed)
PMIC1	382	5.11	1.453	0.164	0.100	−0.164	3.211	0.000
PMIC2	382	4.88	1.451	0.158	0.114	−0.158	3.088	0.000
PMIC3	382	4.65	1.475	0.171	0.114	−0.171	3.346	0.000
PMIC4	382	4.61	1.443	0.169	0.119	−0.169	3.297	0.000
PMIC5	382	4.74	1.405	0.160	0.143	−0.160	3.133	0.000
PMIO1	382	5.15	1.475	0.180	0.105	−0.180	3.510	0.000
PMIO2	382	5.01	1.451	0.174	0.111	−0.174	3.400	0.000
PMIO3	382	4.77	1.473	0.165	0.117	−0.165	3.234	0.000
PMIO4	382	4.91	1.440	0.165	0.115	−0.165	3.230	0.000
PMIO5	382	4.70	1.504	0.168	0.102	−.168	3.277	0.000
FI1	382	4.96	1.843	0.200	0.134	−0.200	3.918	0.000
FI2	382	5.31	1.684	0.208	0.158	−0.208	4.062	0.000
FI3	382	5.36	1.653	0.217	0.160	−0.217	4.241	0.000
PI1	382	5.13	1.787	0.186	0.148	−0.186	3.638	0.000
PI2	382	5.54	1.651	0.252	0.188	−0.252	4.922	0.000

Abbreviations: FI, financial incentives; PI, purchase intention; PMIC, perceived marketplace influence consumers; PMIO, perceived marketplace influence organizations.

[a]Test distribution is normal.

[b]Calculated from data.

TABLE 3 ANOVA test of linearity.

			Sum of squares	df	Mean square	F	Sig.
PI * PMIC	Between groups	(Combined)	5.791	30	0.193	3.110	0.000
		Linearity	3.661	1	3.661	58.999	0.000
		Deviation from linearity	2.129	29	0.073	1.183	0.240
PI * PMIO	Between Groups	(Combined)	5.903	30	0.197	3.188	0.000
		Linearity	4.190	1	4.190	67.875	0.000
		Deviation from linearity	1.713	29	0.059	.957	0.533
PI * FI	Between Groups	(Combined)	8.156	18	0.453	8.471	0.000
		Linearity	6.355	1	6.355	118.814	0.000
		Deviation from linearity	1.801	17	0.106	1.981	0.012

Abbreviations: FI, financial incentives; PI, purchase intention; PMIC, perceived marketplace influence consumers; PMIO, perceived marketplace influence organizations.

TABLE 4 Multicollinearity test: non-standardized and standardized coefficients[a].

	Unstandardised coefficients		Standardized coefficients			Collinearity statistics	
Model	B	Std. error	Beta	t	Sig.	Tolerance	VIF
(Constant)	0.200	0.044		4.493	0.000		
PMIC	0.167	0.069	0.132	2.429	0.016	0.634	1.576
PMIO	0.222	0.068	0.178	3.269	0.001	0.626	1.598
FI	0.388	0.049	0.370	7.861	0.000	0.842	1.188

Abbreviations: FI, financial incentives; PI, purchase intention; PMIC, perceived marketplace influence consumers; PMIO, perceived marketplace influence organizations.
[a]Dependent variable: purchase intention (PI).

Larcker, 1981; Hair et al., 2017). All values exceed the recommended level (see Table 5). Thus, internal consistency and convergent validity are confirmed. In addition, the loadings of each item were analysed. They are significant and greater than 0.7 (Hair, 2011).

Then, discriminant validity was analysed in two ways: Fornell-Larcker criterion and Heterotrait-Monotrait ratio (HTMT). Both pathways showed favourable results according to the literature (see Table 6; Fornell & Larcker, 1981, Henseler et al., 2014).

4.1 | Structural model

The hypotheses of the proposed model were tested using structural equation modelling (SEM) technique with SmartPLS program. The research hypotheses were tested by comparative analysis of the structural coefficients. Bootstrapping analysis was performed with a total of 5000 subsamples randomly extracted from the original data set. In addition, effect sizes (f^2 or Cohen's indicator) were examined. According to Hair et al. (2017), f^2 values greater than 0.35 can be considered strong; values of 0.15, moderate; and 0.02, weak. Table 7 shows the results of all hypotheses tested. The results show that all research hypotheses are supported at 5% level. The strongest relationships are H4 ($\beta_{INT\rightarrow GCE} = 0.751$, p value $= 0.000$; $f^2 = 1.291$) and H3 ($\beta_{FI\rightarrow INT} = 0.379$, p value $= 0.001$; $f^2 = 0.172$). Research hypotheses with the lowest impact are those related to PMI: H2 ($\beta_{PMIO\rightarrow INT} = 0.174$, p value $= 0.007$; $f^2 = 0.027$) and H1 ($\beta_{PMIC\rightarrow INT} = 0.130$, p value $= 0.041$; $f^2 = 0.015$).

The predictive ability of the model was assessed using the multiple squared correlation coefficient (R^2). The value for intention to adopt is 0.301, which means that financial incentives and PMI Consumer and PMI Organization explain 30% of intention to adopt. R^2 for green customer engagement is 0.564, it therefore explains a high proportion of the model's variance.

Lastly, the value of standardized mean squared residual (SRMR) ratio was tested to contrast the difference between the observed correlation and the predicted correlation as an indicator of model fit. The value was 0.049, which is below the recommended value of 0.08 (Henseler et al., 2014, see Figure 2).

Additionally, the proposed behavioural model was tested by differentiating between users who have an internal combustion vehicle ($n = 203$) and those who have an electric vehicle ($n = 150$), whether plug-in hybrid electric, hybrid electric, or electric vehicle. The results show that all hypotheses are significant except in one case for each group. In the case of users who own a fossil fuel vehicle H1 is not significant and in the case of electric vehicle owners H2 is not significant (see Figure 3).

TABLE 5 Standard loadings, composite reliability and average variance extracted.

Constructs and measured items	Standard loadings
Perceived marketplace influence (adapted from Leary et al., 2017): If I purchase environmentally friendly products (like an electric car), or express my views and opinions to others…	
PMI consumer (Cronbach's $\alpha = 0.926$; CR = 0.945; AVE = 0.774)	
My behaviour (i.e., purchasing an electric car or expressing my views and opinions to others) guides other individuals to act in a similar manner.	0.803
I feel what I do sways what others around me do.	0.898
What I choose to do or say impacts what other consumers choose to do.	0.887
My behaviour will cause other consumers to act similarly.	0.909
I know that my behaviour motivates others to act similarly.	0.897
PMI Organization (Cronbach's α = 0.929; CR = 0.947; AVE = 0.780)	
I feel what I buy encourages companies to make and sell environmentally friendly products.	0.879
My behaviour does guide organizations to provide similar products.	0.913
What I do influences the actions of a company.	0.882
The choices I make persuade companies to offer specific products to consumers.	0.892
My behaviour causes companies to change their product offerings and corporate practices.	0.848
Financial incentives (Cronbach's $\alpha = 0.873$; CR = 0.921; AVE = 0.796; adapted from Wang et al., 2017)	
Government rebate on excise duty is attractive to me to purchase a hybrid/electric car.	0.841
Rebate on road taxi s valuable to me to adopt a hybrid/electric vehicle.	0.918
Competitive interest rates by financial institutions for the purchase of a hybrid/electric car is valuable to me.	0.916
Purchase intention (Cronbach's $\alpha = 0.866$; CR = 0.937; AVE = 0.881; adapted from Sahin et al., 2012)	
The electric car is my first choice when purchasing a new car.	0.939
I shall purchase an electric car in the near future.	0.938
Green customer engagement (Cronbach's $\alpha = 0.867$; CR = 0.910; AVE = 0.718; adapted from Pansari & Kumar, 2017; Ullah et al., 2021)	
I say positive things about the environmental benefits of hybrid/electric car to others.	0.901
I recommend a hybrid/electric car to someone who seeks my advice on cars because it is environmentally friendly.	0.917
I often participate in discussions for environmental benefits of hybrid/electric cars.	0.706
Overall, I am pleased with the environmental benefits of my electric car.	0.851

TABLE 6 Discriminant validity.

	FI	GCE	PMI consumer	PMI organization	Purchase intention
FI	**0.892**	0.477	0.386	0.404	0.555
GCE	0.424	**0.848**	0.521	0.586	0.855
PMI consumer	0.352	0.465	**0.880**	0.634	0.406
PMI organization	0.369	0.524	0.588	**0.883**	0.434
Purchase intention	0.489	0.751	0.366	0.390	**0.939**

Note: The diagonal elements are the square roots of AVE. Values below the diagonal elements are the inter-construct correlations (Fornell and Larcker's test) and values above the diagonal elements are HTMT ratio.
Abbreviations: FI, financial incentives; GCE, green customer engagement.

4.2 | ANN results: deep-learning artificial neural network model

One of the shortcomings of PLS-SEM is that, it cannot take into account any potential non-linear effects between inputs and outputs (Kalinić et al., 2019). The results show that the relationship between FI and PI has statistically significant deviation from linearity, which justifies the introduction of ANNs in our research, as an AI technique capable of modelling non-linear relationships among its inputs and outputs (Kalinić et al., 2021). Additional advantages of ANN approach are that ANN models are generally more robust (Singh et al., 2021) and more accurate (Pozón-López et al., 2020) than linear models. However, on the other hand, due to the "black-box" nature of ANN models, they cannot be used

TABLE 7 General model resolution by SmartPLS (bootstrapping = 5000).

Research hypothesis		Path coefficient	SD	t value	p value	f^2	Result
H1 (+)	Perceived marketplace influence consumer → intention	0.130	0.064	2.047	0.041	0.015	Supported
H2 (+)	Perceived marketplace influence organization → intention	0.174	0.065	2.689	0.007	0.027	Supported
H3 (+)	Financial incentives → intention	0.379	0.059	6.472	0.001	0.172	Supported
H4 (+)	Intention → green customer engagement	0.751	0.030	25.211	0.000	1.291	Supported

Abbreviations: APMIC, perceived marketplace influence consumer; FI, financial incentives; GCE: green customer engagement; INT, intention to adopt; PMIO, perceived marketplace influence organization.

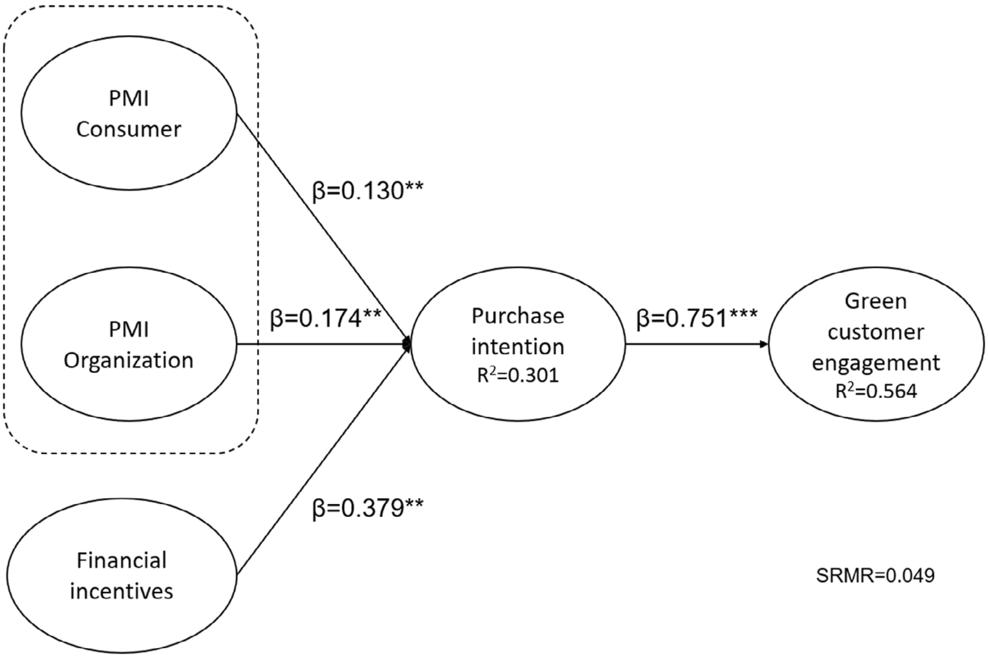

FIGURE 2 Results of the proposed theoretical model by structural equation modelling (SEM) (n = 382). ***p value <0.000; **p value <0.05.

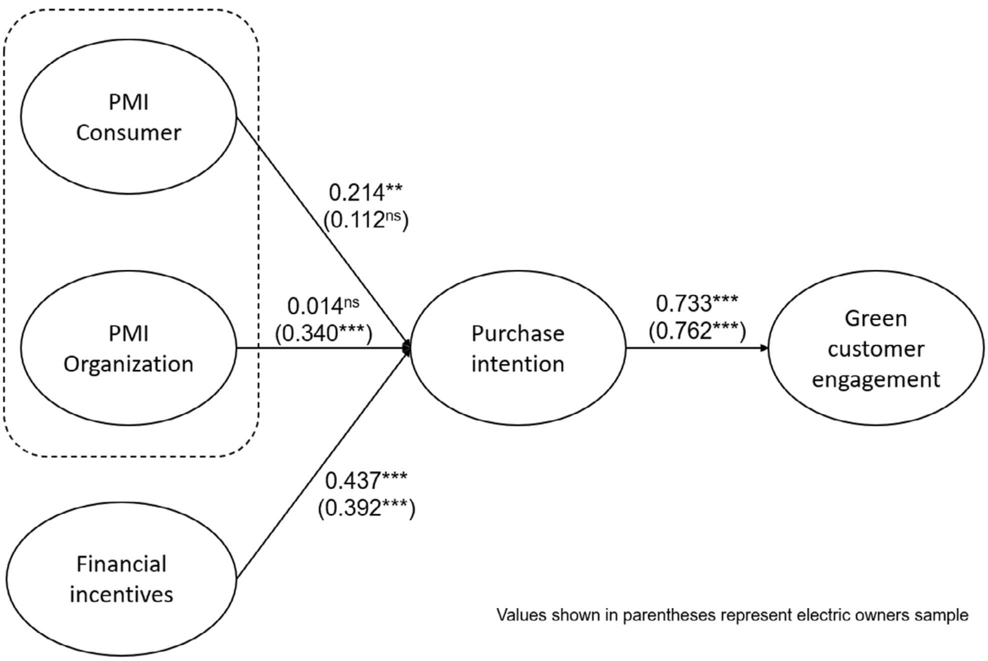

FIGURE 3 Results of the proposed model by structural equation modelling (SEM) for each subsample. ***p value <0.000; **p value <0.05.

TABLE 8 Comparison of main differences between partial least squares (PLS)-structural equation modelling (SEM) and artificial neural network (ANN).

Feature	PLS-SEM	ANN
Multivariate assumptions should be fulfilled	Partially	No
Suitable for hypotheses testing	Yes	No
Suitable for non-linear relationships	No	Yes
Suitable for complex problems and data	Partially	Yes
Explainability	Good	Poor
Accuracy	Good	Excellent

for hypothesis testing (Liébana-Cabanillas et al., 2017; Sternad et al., 2022. The comparison of main differences between PLS-SEM and ANN is presented in Table 8.

Therefore, the introduction of ANNs will complement PLS-SEM in two ways: it will be used to generally reinforce the results obtained by PLS-SEM and to more precisely rank by importance the predictors of PI, which are previously confirmed by PLS-SEM to be statistically significant (Leong et al., 2019; Singh et al., 2021). A review and deeper analysis of the studies based on the two-stage, SEM-ANN approach is presented in Kalinić et al. (2021).

ANNs have a more than 50 years' history, and currently there are many different types in use (Kalinić et al., 2021; Negnevitsky, 2011), but in this research we utilized multilayer perceptron (MLP) with the backpropagation training algorithm, which is one of the most common and most popular ANN models, particularly in technology adoption studies (Kalinić et al., 2021; Leong et al., 2019; Liébana-Cabanillas et al., 2021). A typical MLP-ANN model consists of one input layer, one or more hidden layers and one output layers. Depending on the number of hidden layers, ANNs are divided into "shallow" – with one hidden layer, and "deep"—with two or more hidden layers. Although ANNs with one hidden layer are able to model any continuous function (Negnevitsky, 2011) and most of previous studies employed this sort of the model (Kalinić et al., 2021), "deep learning" ANN models are capable of modelling much more complex dependences (Lee et al., 2020), but require more data for the training. Deep learning ANN models are already successfully implemented in the acceptance studies of medical smartwatches (Almarzouqi et al., 2022), mobile taxi booking apps (Siyal et al., 2021), cryptocurrencies (Abbasi et al., 2021; Alharbi & Sohaib, 2021), exchange of electronic waste (Najmi et al., 2022), wearable payments (Lee et al., 2020), data driven decision making (Ashaari et al., 2021), metaverse (Akour et al., 2022), among others. Therefore, in this research we employed deep learning ANN model with two hidden layers.

The number of neurons in the input layer is equivalent to the number of statistically significant predictors, obtained by PLS-SEM, and in our case it was three (PMIC, PMIO and FI). The number of neurons in the output layer is equivalent to the number of dependent variables, and in our case it was one—PI (there was not much sense to model second sub-model—relationship between PI and GCE, since it would be one input-one output model, and the main purpose of ANN model is to rank the predictors by influence). The number of neurons in both hidden layers was determined automatically, by simulation software—SPSS v20 (Higueras-Castillo, Kalinic, et al., 2020; Kalinic et al., 2019). Finally, sigmoid, as the most common and frequently used activation function (Kalinić et al., 2021; Ooi et al., 2018), was utilized in both hidden and output layers. Figure 4 presents final deep learning ANN model.

When creating a prediction model, there is always trade-off between its complexity and resources needed: more complex models may provide more precise predictions, but usually require more data and processing power. One of frequently raised issues with ANNs is that complex, deep-learning ANN models require significant amount of data for its training. Widrow suggested rule-of-thumb, by which, for example, to achieve an estimation error lower than 10%, the number of training examples should be at least 10 times bigger than the number of adjustable parameters in the ANN model (Negnevitsky, 2011, p. 329). The deep-learning ANN model, used in this study and presented in Figure 4, has 17 adjustable parameters (12 neuron weights and five biases). The dataset consists of 382 data points, out of which 90% are used for the training and remaining 10% are used for testing of deep-learning ANN model (Kalinić et al., 2021; Singh et al., 2021). Therefore, using the aforementioned rule-of-thumb with 17 adjustable parameters and 344 training examples, we may conclude that presented ANN model would have an estimation error lower than 5% that is, that the dataset is large enough to train deep-learning ANN model.

Overfitting is one of the most significant issues in ANN models (Hew et al., 2018; Kalinic et al., 2019), in which complex ANN models tend to simply memorize all training examples and thus lose the ability to generalize, which further leads to low accuracy with previously unseen input data. To prevent it, ten-fold cross-validation procedure was employed (Leong et al., 2019; Sharma et al., 2019). Root mean square of error (RMSE) was used as a common measure of prediction accuracy of ANN models (Leong, Hew, Ooi, & Dwivedi, 2020; Sternad et al., 2019; Wong et al., 2020) and the results of 10 model runs are presented in Table 9.

Low RMSE values for both, training, and testing processes, confirm that the dataset fits the model very well (Leong, Hew, Ooi, & Wei, 2020) and that high predictive accuracy is achieved. The relevance of the predictor variables and the quality of overall model are also confirmed by the fact that all synaptic weights in the model have non-zero values (Anouze & Alamro, 2020), as presented for a sample model run in Table 10.

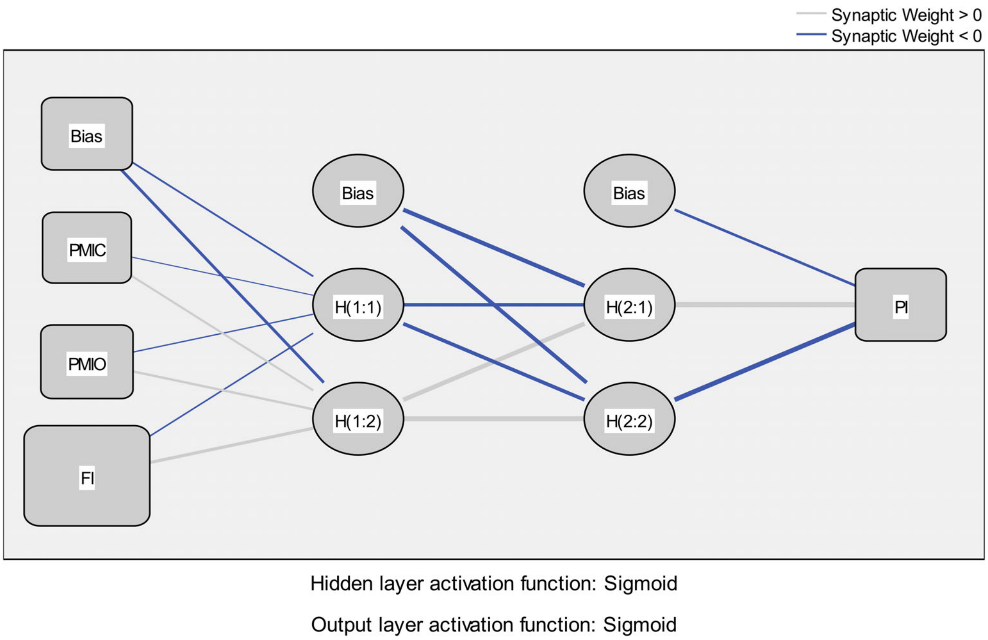

FIGURE 4 Artificial neural network (ANN) model.

TABLE 9 Root mean square of error values of artificial neural networks.

	Inputs: PMIC, PMIO, FI output: PI	
Network	**Training**	**Testing**
1	0.1556	0.1281
2	0.1585	0.1522
3	0.1539	0.1455
4	0.1574	0.1569
5	0.1536	0.1521
6	0.1476	0.1961
7	0.1526	0.1691
8	0.1535	0.1504
9	0.1568	0.1305
10	0.1571	0.1216
Mean	0.1547	0.1502
Standard deviation	0.0032	0.0217

Abbreviations: FI, financial incentives; PI, purchase intention; PMIC, perceived marketplace influence consumers; PMIO, perceived marketplace influence organizations.

The good performance of the ANN model is additionally confirmed by high value of goodness-of-fit coefficient (Leong et al., 2018; Singh et al., 2021), which in our case was $R^2 = 0.943$. Finally, to determine the rank of influence of each predictor, sensitivity analysis was performed by calculating normalized importance of each predictor (Leong et al., 2019; Liébana-Cabanillas et al., 2018), and the results are presented in Table 11.

For comparison, the results of PLS-SEM and ANN analyses are presented together in Table 9. According to ANN results, the most significant predictor of PI is FI, followed by PMIO and PMIC, which is the same order of influence that is, the same ranking as by PLS-SEM results (Table 12). However, ANN results suggest that the influence of PMIC and PMIO is almost the same, which was not the case according to PLS-SEM results. In addition, by ANN results, the influence of PMIC and PMIO is approximately the half of PI influence, which again is different compared to the analysis of path coefficients obtained by PLS-SEM. These findings are also supported by the total contribution of the input neurons (Leong et al., 2019; Philips et al., 2015). Presented minor differences between PLS-SEM and ANN results are the consequence of the higher prediction accuracy of the ANN model, which is able to take into account existing non-linear effects among variables (Sternad et al., 2022).

TABLE 10 Biases, neuron weights and total contribution.

Predictor		Predicted Hidden layer 1 H(1:1)	H(1:2)	Hidden layer 2 H(2:1)	H(2:2)	Output layer IU	Total contribution
Input layer	(Bias)	−1.671	−2.832				4.503
	PMIC	0.638	1.068				1.706
	PMIO	0.891	0.954				1.846
	FI	1.765	1.924				3.689
Hidden layer 1	(Bias)			−2.912	−0.441		
	H(1:1)			1.322	0.936		
	H(1:2)			3.054	0.969		
Hidden layer 2	(Bias)					−1.373	
	H(2:1)					4.541	
	H(2:2)					1.163	

Abbreviations: FI, financial incentives; PI, purchase intention; PMIC, perceived marketplace influence consumers; PMIO, perceived marketplace influence organizations.

TABLE 11 Neural network sensitivity analysis.

Network	Relative importance PMIC	PMIO	FI
1	0.248	0.234	0.518
2	0.202	0.236	0.562
3	0.252	0.255	0.494
4	0.306	0.257	0.437
5	0.208	0.316	0.476
6	0.258	0.232	0.510
7	0.273	0.206	0.520
8	0.230	0.263	0.506
9	0.207	0.306	0.487
10	0.280	0.209	0.511
Average importance	0.246	0.251	0.502
Normalized importance (%)	49.1	50.1	100.0

Abbreviations: FI, financial incentives; PI, purchase intention; PMIC, perceived marketplace influence consumers; PMIO, perceived marketplace influence organizations.

TABLE 12 Comparison between partial least squares (PLS)-structural equation modelling (SEM) and artificial neural network (ANN) results.

Path	Path coefficient (PLS-SEM)	Normalized importance % (ANN)	Ranking (PLS-SEM)	Ranking (ANN)
PMIC → PI	0.130	49.1	3	3
PMIO → PI	0.174	50.1	2	2
FI → PI	0.379	100.0	1	1

Abbreviations: FI, financial incentives; PI, purchase intention; PMIC, perceived marketplace influence consumers; PMIO, perceived marketplace influence organizations.

5 | CONCLUSION AND POLICY IMPLICATIONS

5.1 | Theoretical implications

In recent years, all studies related to the future development of our planet point out that humanity is in danger. The decline in the quality of ecosystems augurs that it will be difficult to maintain human progress (Steffen et al., 2015). The excesses carried out by the most developed countries foretell a major global destabilization. Efforts in different fields include the development of new products and the growing interest in so-called pro-environmental behaviour. In this line, it has been shown that such behaviour produces a series of positive consequences both for the environment and for the individual himself, which spreads the realization of environmentally friendly actions (Vanegas-Rico et al., 2018). Studies reveal that there is an increase in awareness and a shift in behaviour towards sustainable products (Agnisarman et al., 2018). Environmentally sustainable purchasing decisions provide the potential to reduce pollution through the adoption of environmentally friendly products. For such reasons, the use of new cleaner technologies and a more environmentally friendly culture are being promoted. In this sense, electric vehicles are configured as an environmentally sustainable technology that requires an in-depth analysis to understand the determinants of their purchase in our society.

Using a double methodology this research analyzes the importance of a set of antecedents of the purchase intention of electric cars and how it determines the green consumer engagement. Precisely, some previous studies have confirmed the differences between attitude and behaviour, so our research has tried to reduce this gap by studying the concepts of Perceived Marketplace Influence (PMI) and financial incentives. In this respect, all the hypotheses proposed in the research have been confirmed.

First, a model obtained with PLS-SEM showed adequate psychometric properties both for the measurement model (in terms of reliability and convergent and discriminant validity) and for the structural model used to test the proposed research hypotheses. The estimated model shows that financial incentives was the most important determinant of the intention to purchase electric vehicles in the analysed sample. The results show that, external incentives offered for the acquisition of vehicles of this nature are determinants of buyers' purchase decisions (Jenn et al., 2018). As in previous studies financial incentives are the key motivating factor for electric vehicle adoption (Ghasri et al., 2019; Mpoi et al., 2023; Verma et al., 2020). Second, the importance of the two-dimensional PMI construct is also confirmed (Leary et al., 2017), and the PMIO dimension had a slightly higher impact than the PMIC dimension. In this sense, it seems to be confirmed that when faced with a purchase decision for a product of this nature, the utilitarian dimension associated with the first of the dimensions is more important than the hedonic dimension associated with the second of the proposed dimensions (Leary et al., 2019).

From this first analysis, a neural network analysis was included to classify the relative influence of the significant predictors of purchase intention obtained by PLS-SEM. On this occasion, the results suggest that in the ANN analysis the influence of PMIC and PMIO is almost the same, which was not the case according to the results of the first technique used. Moreover, according to the ANN results, the influence of PMIC and PMIO is about half the influence of purchase intention, which is also different compared to the analysis of path coefficients obtained by PLS-SEM. These small differences are a consequence of the higher prediction accuracy of ANN models as they can account for existing nonlinear effects between variables (Kalinić et al., 2021).

5.2 | Managerial implications

This study establishes some conclusions that can be applied to the business environment. In this regard, given that this type of vehicle is still at an incipient stage in many countries, it will be essential to identify the most important factors driving the adoption of electric vehicles among potential users (Tunçel, 2022). This is an elementary step in product adoption. It is suggested to establish stable incentive schemes as they have been shown to increase product sales (Münzel et al., 2019). Likewise, private companies should encourage this by establishing their own incentive scheme. The subsidies boost purchases and diminish the negative perception of a high price. Even consumers understand that the new technology bears a higher price than other substitute products, they may also perceive that the long-term economic benefits offset the high initial price (Khazaei, 2019). However, it is recommended to continue to support consumption with monetary and non-monetary support measures, otherwise the transition would probably be even slower. In this regard, the income level of the consumer is a determinant as well as the place of residence of the consumer (Higueras-Castillo et al., 2022).

In addition, it is considered fundamental to analyse the importance of the PMI in both dimensions because of the implications it has since it reaffirms the importance of beliefs in the ecological decisions of customers. Precisely this value of PMI can act as an important basis for segmenting customers, since people with a high PMI are more likely to buy green products because of the importance of their utilitarian and hedonic decisions. In this sense, it will be essential to establish communication campaigns that establish those values that users consider fundamental in the purchase decisions of this type of vehicles (Joshi et al., 2021).

The creation and application of alternative, hybrid, and electrified technologies may offer a key path for transformation in the transportation sector in addressing environmental issues and the depletion of natural resources (Bleijenberg et al., 2013). This is of relevance to Mauritius, which has been adversely affected by climate change, in recent years. The rising sea level and erosion of beaches represent a serious threat to the future of the tourism sector of the island, one of the major economic pillars.

A behavioural change in the consumption pattern of consumers favouring eco-friendly products is required. The commitment of the ecological customer is demonstrated when the intention to purchase electric vehicles improves, so that both brands and governments should pay more attention to achieving sales of this type of vehicles to improve the commitment to a product for its environmental value and consequently our environment remains protected (Abou-Shouk & Soliman, 2021). Green campaigns will create awareness, which will be embraced by these people and will create a multiplier effect as others will follow. This presents a large potential for brands producing electric cars.

5.3 | Limitations and future lines of research

Despite the contributions that have been explained, this study has several limitations that offer the possibility of new avenues of research. First, the study focuses on a sample of Mauritanian users to assess the purchase intention of a novel and sustainable technology such as electric vehicles and its effect on customer green engagement as well as the factors that influence their purchase. Moreover, this study could serve as a basis for research in other countries where the level of adoption and acceptance of this technology is different from the proposed country, examining the cultural differences at play.

This research only proposes the analysis of the PMI variable and that of financial incentives in the adoption of electric vehicles, but additional variables could have been included for a more complete understanding of the adoption of this sustainable technology related to the level of innovation of potential buyers or the ecological identity that they manifest in their environment. In addition, future research could include the moderating effect of sociodemographic variables that would allow effective segmentation of potential buyers of these vehicles, for example, gender, age, experience, and income level.

In relation to the methodology used, it is proposed to implement the use of neuromarketing methodologies, such as functional magnetic resonance imaging (FMRI) or electroencephalogram (EEG) and to triangulate these techniques.

Finally, the cross-sectional nature of the data collection method employed in our research prevents us from adequately assessing the evolution of user behaviour. In this sense, a longitudinal approach would be even more appropriate, as it would allow us to test the reliability and robustness of the various relationships and constructs proposed in this study by examining behaviour over time.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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