The Influence of Society on the Behavioural Intention to Use a Technology: Evidence from the Battery Electric Vehicles Domain

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Abstract

The widespread adoption of battery electric vehicles (BEVs) could be one of the most effective ways to reduce harmful emissions and meet consumers' transportation needs. Their market penetration, however, is below expectations. Societal influence on individual behaviour has been a central concept in literature and suggested as a key to enhancing the uptake of technology-driven products (Ajzen, 2020; Rogers, 2003; Venkatesh, Thong and Xu, 2016). As technology adoption becomes increasingly social, it is essential to consider the influence of societal factors on consumers' intentions to use technology. This paper examines the effects of *subjective norms* and *image* on the behavioural intention to adopt BEVs. Data collected from 120 self-administrated surveys of Macau residents were analysed using structural equation modelling (SmartPLS). The assessment indicated that respondents tend to be influenced by social factors in their decision to adopt BEVs. In particular, the results showed positive and significant relationships between social norm, image and behavioural intention. The image construct emerged as a strong predictor, and the effects were particularly relevant for the group of BEV owners. The paper underlines that social elements should be integrated into communication strategies as they play essential roles in the decision to adopt a technology. Further, image is suggested as a factor to be included in research frameworks since the construct appears to be a relevant predictor of intention, especially in contexts where the choices that consumers make are public and subject to judgments from the members of society. Finally, the study's limitations and the need for future research are also discussed.

Keywords: Subjective norm, Image, Social influence, Battery electric vehicles, Structural Equation Modelling.

1. Introduction

Battery electric vehicles (BEVs) - i.e., vehicles that run solely on electricity and promise zero tailpipe emissions - are a major technological trend that can potentially contribute to reducing pollution, noise, and exploitation of non-renewable resources (Thomas, Michael and Joy, 2022). Even though global BEV sales are rising (Conway et al., 2021), the Statistic and Census Service estimated that in Macau, less than one per cent of the total vehicles circulating in 2020 were fully electric (DSEC, 2022).

When explaining the slow diffusion of electric vehicles, the literature points to the high purchase price as the main barrier to adoption (Krishna, 2021). A recent study reported that among the elements of the marketing mix, the price had the strongest influence on customers' purchase intention (Shafiee and Shahin, 2021). Indeed, full battery-electric technology doesn't come cheap. In early 2022, a Tesla Model 3 long-range variant (a fully electric, dual-motor vehicle) was sold in Macau for MOP$425,200 (US$52,650) (Tesla, 2022). Priced at this level, the car targets a wealthy segment of technology enthusiasts. Macau is one of the wealthiest places in the world (Fraser, 2018). It is a top destination in South East Asia, where gambling is the pillar of the economy (Lampo and Lee, 2011) and is responsible for the unprecedented well-being of the population.

If we consider that the purchase price may not be the main barrier to BEV adoption, the question remains as to why electric vehicles aren't widely diffused in Macau. According to Rogers (2003), diffusion is the process by which information about an innovation flows from one person to another. The final result is the adoption (or rejection) of that innovation. Thus, the social system identifies the boundary in which the diffusion of innovation occurs.

Society's influence is pervasive in human social interaction, as individuals often modify their opinions, attitudes, beliefs, or behaviour to resemble those of others (Flache et al., 2017). Venkatesh, Thong and Xu (2016) noted that the opinions and expectations of others heavily influence the adoption of technology innovations, and consumers tend to modify their behaviour accordingly. The influence of society on individuals' decisions has been long discussed in the literature (Ajzen, 2020; Rogers, 2003; Venkatesh et al., 2012) and suggested as an effective approach to enhance consumers' adoption of technology-driven products and services (Sakkthivel and Ramu, 2018; Viswanathan, Singh and Gupta, 2020). Furthermore, considering that the adoption process is also influenced by how users perceive the technology (Issac, Mathew and Sriram, 2022; Rogers, 2003), explaining acceptance is a complex task, as behaviour can be approached at many different levels (Fishbein and Ajzen, 2011).

Understanding how society shapes individual behaviour is important to practitioners and marketers. Studies, however, have been focusing on the core technical characteristics of innovations to explain the factors that influence acceptance and use. While TAM-2 (Venkatesh and Davis, 2000) and TAM-3 (Venkatesh and Bala, 2008) assess the factors of social norm and image as antecedents of behaviour, mainstream frameworks typically examine subjective norm (Ajzen, 2020) or social influence (Venkatesh et al., 2016) alone. Additionally, except in a few studies (Axsen and Kurani, 2012; Griskevicius, Tybur, and Van den Bergh, 2010; Jeon, Yoo and Choi, 2012), the effects of society on individuals' intention to adopt BEVs are mainly unexplored. This study investigates how the social factors of subjective norms and image determine the behavioural intention to adopt battery-electric technology in a sample of Macau residents. It is generally recognised that Macau has great potential for the transition to electric mobility due to the small size of the territory and the availability of financial resources (Lai et al., 2015). Additionally, since BEVs have zero tailpipe emissions, their widespread adoption could reduce air pollutants and positively impact people's health and the tourist image of the city. As technology adoption becomes increasingly consumer-driven and social (Graf-Vlachy, Buhtz and König, 2018), a better understanding of the relationships between social factors and behavioural intention provides practitioners and marketers with more theoretical foundations in a new market.

2. Literature Review

The influence that members of a social system have on others is an important factor in technology acceptance that deserves special attention. Shin and Biocca (2018) presented empirical evidence that behavioural intention is strongly associated with social predictors. According to Rogers (2003), innovations spread because the social system affects their diffusion in several ways. The central idea is that behaviour is influenced by how individuals believe others will view them (e.g., positively or negatively) due to having used a technology (Venkatesh et al., 2012). This concept has been studied under several labels. Ajzen (2020) used the term *subjective norms* to refer to the perceived social pressure to behave in a specific manner. Triandis (1980) called *social factors* the individual's internalisation of the reference groups' subjective culture. Thompson et al. (1991), building on Triandis' work, used the term *social norms*. Venkatesh (2021) named *social influence* as the degree to which an individual perceives that important others believe they should use a new system. The antecedents of subjective norms are the corresponding beliefs. Such beliefs originate in various ways and may also be wrong or inaccurate. Once beliefs are formed, they will guide individuals' decisions (Fishbein and Ajzen, 2011). As a general rule, the more favourable the subjective norm is concerning a specific behaviour, the stronger an individual's intention to perform that behaviour. The rationale for the direct effect of the social norms on behavioural intention is that people may choose to perform a specific behaviour even if they are not favourable, as long as they perceive sufficient pressure from society. In studies on the adoption of electric vehicles, the subjective norm was found to be one of the most important determinants of behaviour (Kassim et al., 2017).

Individuals also respond to social normative influences to establish or maintain a favourable image within a reference group (Graf-Vlachy, Buhtz and König, 2018). The notion of the image is rooted in Innovation Diffusion Theory (IDT) (Rogers, 2003) which suggests that the desire to gain social status is an important motivation for adopting a technology innovation. Moore and Benbasat (1991) defined image as the degree to which the use of an innovation is perceived to enhance one's status in the social system. Rogers (2003) considered the image to be an important component of the *relative advantage* of innovations, defined as the user's perception that innovation is superior to the incumbent technology. Moore and Benbasat (1991) argued that the effects of the image are distinct from those of relative advantage, so the image should be considered a separate construct. In addition to IDT, the image concept has been included in TAM-2 (Venkatesh and Davis, 2000) and TAM-3 (Venkatesh and Bala, 2008) to capture the identification effect of social influence in technology research.

Additionally, these frameworks postulate that subjective norms positively influence the image construct. Thus, if important members of an individual's social network believe that they should adopt a specific technology (e.g., using BEVs to reduce air pollution), performing that behaviour will tend to elevate the individual's standing within the social network. In the same direction, Kwee-Meier et al. (2016) found that image aspects positively influence technology acceptance.

Research agrees that consumers are often driven by social factors (Jeon et al., 2012), image gains (Shanmugavel, Alagappan and Balakrishnan, 2022), reputational benefits (Griskevicius et al., 2010), and status motives (Di and Su, 2021) in their choice of vehicles. Similarly, purchases are frequently associated with traits of uniqueness, symbolism, and innovation (Wang et al., 2022) that bring social prestige to the consumer (Nabi, O'Cass, and Siahtiri, 2019). Although social predictors are significant determinants of intention, the results are limited. As a social system's influence on its members is a complex concept with ample potential for research (Graf-Vlachy, Buhtz and König, 2018), the underlying relationships must be understood better. For this purpose, a conceptual model and research hypotheses are presented in the following section.

3. Conceptual Model

The study was built on a model of three constructs from the literature review: social norm, image and behavioural intention. More precisely, social norm (SN) and image (IM) represented the independent variables, while the behavioural intention (BI) to use battery electric vehicles was the dependent variable.

The items for the construct BI were adapted from Venkatesh et al. (2003), items for SN from Venkatesh, Thong and Xu (2012), while items for IM were adapted from Moore and Benbasat (1991). In line with Venkatesh and Davis (2000) and Venkatesh and Bala (2008), a positive relationship between subjective norms and image was also assessed in the model. The following figure illustrates the conceptual model, while the related hypotheses are summarised in Table 1.

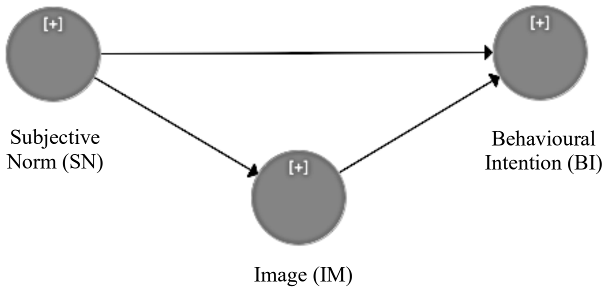

Figure 1. Conceptual model.

Table 1: Summary of Hypotheses.

H1	A positive and significant relationship exists between subjective norm (SN) and behavioural intention (BI).
H2	A positive and significant relationship exists between image (IM) and behavioural intention (BI).
H3	A positive and significant relationship exists between subjective norm (SN) and image (IM).

4. Methodology

The study adopted a descriptive approach (Kolb, 2022), a cross-sectional look at the influence of social norms and image on the behavioural intention to adopt BEVs technology. A self-administrated survey with established and validated scales was considered the most suitable instrument for gathering data. Items related to behavioural intention and social norm constructs were adapted from Venkatesh et al. (2012), while those for the image from Moore and Benbasat (1991). The items were grouped according to their construct and assessed using a 7-point Likert scale with anchors ranging from 1 (strongly disagree) to 7 (strongly agree). Demographic variables were also included to capture respondents' gender, age, education, income and type of vehicle. The survey was initially developed in English and then translated into traditional Chinese using the back-translation technique to facilitate understanding (Son, 2018). The survey opened with a screening question related to the ownership of a motor vehicle to prevent unqualified respondents from being included in the study.

Regarding the minimum sample size for a study, Field (2013) noted that common rules suggest between 10 to 15 observations for each predictor in the model. This work adopted G*Power (Erdfelder, Faul, and Buchner, 1996) to determine the necessary number of observations required to achieve a satisfactory power level. Accordingly, taking into consideration multiple regressions (settings: .15 effect size, .05 probability error, .80 power, and two predictors in the model), the software returned 68 cases as the recommended sample size. The questionnaire was made available by using an online surveying platform. Responses were collected by sending a link via WeChat (the most popular instant messaging tool in Macau) to potential participants in the authors' network. In contrast, others were collected in person by using a tablet that was set up for this purpose.

The target population consisted of Macau residents possessing a vehicle for private use. To facilitate the data gathering, participants were initially selected from the researchers' networks and by the snowball method (Flick, 2018), assuming that respondents were similar to the target population. The participants were informed about the purpose of the research and assured about the anonymity of their responses. Participation was voluntary, and no payment was offered. Ultimately, 120 responses were collected and deemed usable for further analysis.

5. Discussion of Results

SmartPLS v.3.3.9 was used to perform the data analysis. Hair et al. (2022) observed that PLS-SEM is recommended to assess models with small samples and should be preferred over CB-SEM when prediction and theory development are part of the study. Before running the PLS algorithm, possible issues with the data (e.g., missing values, outliers, non-normality, and multicollinearity) were assessed and found not to be a source of concern. Additionally, the assessment of VIF values, as discussed in Kock (2015), excluded common method bias.

5.1 Respondents Details

The result showed that the majority of the respondents were male (54.17%), aged between 25 to 34 years old (35%), held a bachelor's degree (56.67%), and with an income of MOP 20,000 to 35,000 (ca. US$ 2,460-4,300) per month (55.49%). Most of the individuals reported owning an Internal Combustion Engine (ICE) vehicle (76.67%), followed by Hybrid Electric Vehicles (HEV) (13.33%) and Battery Electric Vehicles (BEV) (10%). Table 2 summarises the demographic characteristics of the respondents.

Table 2: Summary of respondents' profiles.

Demographic Profile	Description	Frequency	Percentage (%)
Gender (n=120)	Male	65	54.17%
	Female	55	45.83%
Age (n=120)	18-24	28	23.33%
	25-34	42	35.00%
	35-44	30	25.00%
	45 and above	20	16.67%
Education (n=120)	High School	10	8.33%
	Bachelor Degree	68	56.67%
	Higher Education	28	23.33%
	Other	14	11.67%
Monthly Income (n=106)	< MOP 20,000; US$2,460	26	24.53%
	MOP 20,000-35,000; US$ 2,460-4,300	62	55.49%
	> MOP 35,000; US$4,300	18	16.98%
Type of Car (n=120)	Internal Combustion Engine (ICE)	92	76.67%
	Hybrid Electric Vehicle (HEV)	16	13.33%
	Battery Electric Vehicle (BEV)	12	10.00%

Source: Researchers' table.

5.2 Evaluation of PLS-SEM Results

The initial evaluation showed that our model explained 36,0% (R^2= 0.360) of the variance of the endogenous variable BI. However, to interpret the findings correctly, Hair et al. (2022) recommended a 2-step procedure: first, the researcher needs to address the measurement model (outer model), which includes the relationships between the latent constructs and the associated indicators. In the next step, the researcher needs to examine the structural model (inner model), which involves testing the proposed hypothesis and evaluating the relationships among variables. Tests for indicator reliability and validity were performed to determine whether the construct indicators measured the same concept and differed from the other constructs. The analysis showed that all measurements were within the recommended thresholds. The following table summarises the construct's reliability and validity.

Table 3: Constructs reliability and validity.

Construct	Items	Loadings	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Behaviour Intention	BI1	0.741	0.760	0.764	0.863	0.679
	BI2	0.843				
	BI3	0.881				
Social Norm	SI1	0.875	0.864	0.936	0.915	0.783
	SI2	0.835				
	SI3	0.884				
Image	IM1	0.927	0.833	0.845	0.899	0.748
	IM2	0.882				
	IM3	0.844				

Evaluation criteria: Loadings >0.70; Cronbach's Alpha: >0.70; Rho_A: >0.70; Composite Reliability: >0.70; AVE: >0.50.

The discriminant validity was assessed using the heterotrait-monotrait (HTMT) ratio of correlations. According to Hair et al. (2022), it is the preferred method over the Fornell-Larcker criterion or the assessment of cross-loadings in PLS. As all the results were below the conservative threshold of 0.85 (Henseler et al., 2015), it was concluded that the constructs were significantly different. The following table reports the HTMT values.

Table 4: Heterotrait-monotrait (HTMT) ratios

	BI	IM	SN
BI	-		
IM	0.645	-	
SN	0.418	0.134	-

Evaluation criterion: Evaluating Criterion: HTMT<0.85 (Hair et al., 2022).

After successfully assessing the measurements model, the analysis could continue to evaluate the structural (inner) model. The constructs' VIF values were examined to establish that collinearity issues did not bias the regression results. In our case, VIF values ranged between 1.317 and 2.398 and, therefore, below the recommended value of 3.0 (Hair et al. 2022). The model explained 36% of the construct variance (R2 = 0.360) when considering the target variable BI, which is a weak to moderate explanatory power, according to Hair et al. (2022). However, the result was considered satisfactory because the model consists of only two independent variables. On the other hand, the assessment of the construct IM reported an R^2 of 0.016 (1,6%), which is negligible. In our model, the relationships IM→BI (β= 0.493) and SN→BI (β= 0.303) resulted particularly strong, and despite the relationship SN→IM (β = 0.086) being positive, the bootstrap routine did not substantiate this result. Then, to evaluate whether an omitted construct had a substantial impact on the target variable BI, the f^2 effect size was calculated. Guidelines suggest that values of 0.02, 0.15, and 0.35 represent small, medium, and large effects (Cohen, 1988). In our model, medium to large effect was reported for the relationships IM→BI (0.275) and medium effect for SN→BI (0.151), thus indicating that these relationships had an impact on behavioural intention to use the technology. Although positive, the relationship SN→IM (0.016) could be considered negligible. To conclude the assessment, the goodness-of-fit measure was evaluated. A recently introduced measure of quality fit in PLS-SEM is the standardised root mean square residual (SRMR) (Garson, 2016), although there are notes of caution in using fit measures in a PLS-SEM context (Hair et al., 2022). By convention, SRMR values of less than 0.10 are considered a good fit (Garson, 2016). Our model reported a value below the indicated threshold (SRMR = 0.082); therefore, model fit was established.

Recognising that a PLS path model is useful if it produces generalisable findings, our study also examined the Stone-Geisser's Q^2 value, an indicator of the model's out-of-sample predictive power (Hair et al., 2022). In PLS, the Q^2 value builds on the blindfolding procedure, a sample reuse technique that omits predetermined data points and estimates the parameters with the remaining data. By convention, Q^2 values larger than 0 suggest that the model exhibits predictive relevance for a certain endogenous construct. In our model, the Q^2 predicted value for the BI target construct was larger than 0 (Q^2= 0.228), thus indicating the predictive relevance of the model.

5.3 Analysis of the Constructs

The mean value of the construct behavioural intention (M=4.15, SD=1.30) and the assessment of the related items suggested that even though the adoption of BEVs could come at a later stage, most respondents had favourable intentions toward the technology. Concerning subjective norms (M=3.21, SD=1.18), the data indicated that respondents tend to be moderately influenced by the norms of society when it comes to adopting BEVs. This finding is somehow different from the literature, which endorses the key role of the construct as a determinant of behaviour (Ajzen, 2020; Venkatesh et al., 2016). The mean of the image construct (M=3.38, SD=1.40) indicated that the respondents perceived the effects on the behavioural intention to adopt the technology to some extent. However, the strong PLS path (β= 0.493) suggested that those individuals with a higher image perception exhibited greater behavioural intention towards the technology. Worthy of note is the mean and standard deviation difference between item IM1 and items IM2 and IM3. When this is the case, Shmueli et al. (2016) suggested investigating the matter in subsequent studies by adding qualitative questions and assessing the responses' discrepancies. The following table reports the results.

Table 5: Items of Subjective Norm.

	Item	Mean	SD
BI1	I intend to use BEVs in the future	4.38	1.23
BI2	I predict that I would use a BEV	4.06	1.36
BI3	I plan to use BEV soon	4.02	1.30
SN1	People who are important to me would think that I should use BEVs	3.18	1.24
SN2	People who influence my behaviour would think I should use BEVs	3.26	1.09
SN3	People whose opinion I value would prefer I use BEVs	3.20	1.20
IM1	People in my network who use BEVs have more prestige than those who do not	3.96	1.62
IM2	People in my network who use BEVs have a high profile	3.08	1.31
IM3	Having a BEV is a status symbol in my network	3.12	1.26

Source: Authors' table

Regarding differences among groups, independent t-test analysis showed that men (M=4.22, SD=1.33) scored higher than females (M=3.99, SD=1.28) about their intention to adopt BEVs. However, this difference was not significant ($t_{(118)} = 0.713$, p=0.477). Similarly, One-Way ANOVA analysis indicated that there were no significant differences in age ($F_{(4, 115)}$=0.734, p=0.571) and education ($F_{(4, 115)}$=0.354, p=0.840.05). However, the analysis reported a significant difference related to the variable income ($F_{(4, 98)}$=2.666, p=0.037), a finding suggesting that the BEVs available in the market are accessible to a public of wealthy technology enthusiasts.

Additionally, ANOVA and post hoc comparisons were used to test significant differences in subjective norms and image among the subgroups of vehicle owners (BEV, ICE, and HEV). Due to the difference in sample size among these subgroups, Hochberg's GT2 procedure was used (Field, 2013). The result showed that the mean of the image in the subgroup of BEV owners differed significantly across groups ($F_{(2,117)}$=7.285, p=0.001), thus suggesting a customer segment with peculiar characteristics worth investigating further. The following table reports the result of the multiple group comparisons.

Table 6: Multiple Comparisons.

Dependent Variable	(a) Car Type	(b) Car Type	Mean Difference (a-b)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Image (IM)	BEV	ICE	1.607*	.421	.001	.587	2.627
		HEV	1.466*	.524	.018	.197	2.735
	ICE	BEV	-1.607*	.421	.001	-2.627	-.587
		HEV	-.141	.372	.974	-1.041	.759
	HEV	BEV	-1.466*	.524	.018	-2.735	-.197
		ICE	.141	.372	.974	-.759	1.041
Subjective Norm (SN)	BEV	ICE	-.249	.300	.791	-.974	.477
		HEV	-.361	.373	.704	-1.264	.541
	ICE	BEV	.249	.300	.791	-.477	.974
		HEV	-.112	.264	.964	-.753	.528
	HEV	BEV	.361	.373	.704	-.541	1.264
		ICE	.112	.264	.964	-.528	.753

*. The mean difference is significant at the 0.05 level.

5.4 Assessment of the Hypotheses

The standardised path coefficients among latent variables and their significance were examined to evaluate hypotheses. The construct social norm was positively and significantly related to the behavioural intention to use BEVs, thus leading us to accept hypothesis H1. Similarly, the image construct was positively and significantly associated with the target variable BI, and hypothesis H2 was supported. While subjective norm and image exhibited a positive relationship, the bootstrap routine did not validate the result, so hypothesis H3 was rejected. The following table summarises the results.

Table 7: Assessment of hypotheses.

Hypothesis	Path	Coefficient	t-Value	p-Value	Support
H1	SN→BI	0.302	3.986	0.000	**YES**
H2	IM→BI	0.493	6.069	0.000	**YES**
H3	SI→IM	0.086	1.082	0.528	**NO**

Hypotheses evaluation criteria: t-Value>1.96; p-Value<0.05 (Hair et al., 2022).

6. Conclusion

This work investigated the impact of social factors, namely subjective norms and image, on the behavioural intention to use battery electric vehicles in the context of Macau. The assessment is relevant as individuals tend to modify their behaviour based on the influence that others have on them (Ajzen, 2020; Graf-Vlachy, Buhtz and König, 2018). For this purpose, a sample of Macau residents owing a motor vehicle was analysed using structural equation modelling and statistical software.

Macau residents, on average, expressed positive intention toward the technology, even though BEV adoption might be a long way off. More precisely, the study showed that our model explained 36% of the variance in the target construct, a satisfactory result considering a framework based on two independent variables. The analysis also supported the explanatory and predictive accuracy of the paths in the model.

A positive and significant relationship was observed between the constructs of social norm and image concerning the behavioural intention to use the technology. In our study, image resulted as the strongest predictor of intention. Although a positive relationship was confirmed between social norm and image, the analysis did not substantiate the significance of this result. This finding is somehow different from Venkatesh and Davis (2000); a possible explanation is that social influence may not substantially impact image as the large majority of people have neither adopted BEVs nor recognised the benefits of the technology. Although respondents did not perceive the effects of subjective norms on their social standing, it may well be expected that the impact of the social norm on the image will become increasingly relevant over time as residents get familiar with the technology. As a result, two of the three proposed hypotheses were supported by data. Our analysis reported stronger image effects for the category of BEV owners compared to other groups (HEV, ICE), thus suggesting the peculiar characteristics of this segment. No significant group differences in terms of age, gender and education were found regarding behavioural intention, except for the income variable. The BEV owners could explain this occurrence by including relatively wealthy technology-driven customers, as their high income allows them to be early adopters of the technology. The image construct was highly corroborated in our study. In particular, the analysis indicated that those individuals particularly sensitive to image appeals were more likely to adopt a BEV. In line with Rogers (2008), it could be expected that technology with a higher image score is perceived as more advantageous by potential adopters and therefore accepted faster.

In addition to recognising the relevance of social norms, our study suggested that the image construct may perform well in technology frameworks as a direct determinant of behaviour. The theoretical contribution is apparent; this approach is different from TAM-2 (Venkatesh and Davis, 2000) and TAM-3 (Venkatesh and Bala, 2008), where the construct of image is used to predict perceived usefulness (PEU) and indirectly behavioural intention. Hence, by using the image as a direct predictor of behaviour, researchers could be able to better understand the antecedents and dynamics of behavioural intention. Our study brings relevant managerial contributions as well. When encouraging consumers to adopt new technologies, marketers should consider social factors in developing product communications strategies. It is reasonable to assume that social factors may strengthen over time once the BEV technology spreads further among the members of society. Therefore, marketers should take advantage of subjective norms and image factors to reinforce the adoption process. For instance, they could identify local reference groups and opinion leaders able to positively influence consumers towards specific products and create pressure to conform. Celebrities and influencers should be used to support the adoption of BEVs, a technology that could be marketed as a *socially desirable lifestyle*. As Kotler and Armstrong (2013) noted, reference groups like family, friends, and colleagues may influence people's decision to adopt the technology. Further, image motives could be used to segment and target status-seeking customers that wish to be perceived as modern, trendy and technology savvy in their social network. In addition to the BEV domain, the constructs of subjective norm and image could be relevant in any context where the choices that consumers make are visible by the community members and therefore subject to judgments, such as mobile phones, tablets, and wearable devices technology, among others.

7. Limitations and Future Research

Our findings offer insights into social norms and image determinants of behavioural intention, but some limitations must be addressed. Firstly, the design opted for a convenience sampling method assuming that respondents were similar to the overall target population, which may not be the case. Also, the study focused on the behavioural intention to adopt BEV technology at a single point in time. It did not evaluate how social norms and image influence the actual use of the technology. More importantly, there are cues that the effects on behaviour tend to be stronger for the category of BEV owners. In our case, however, the statistical tests were hampered by the limited size of this subgroup. To address the above limitations, future studies should consider using probability sampling techniques and adopting a longitudinal approach to assess how behavioural intention extends to technology usage. Also, researchers could consider qualitative questions to identify possible issues with the data, as in Shmueli et al. (2016). However, in particular, future research should include a larger sample of BEV adopters to allow the use of advanced statistical techniques.

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