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The role of environmental concern and technology show-off on Electric vehicles adoption: The case of Macao

ABSTRACT

Purpose: When it comes to Battery Electric Vehicles (BEVs), research has typically considered the construct of environmental concern a key determinant of behavioral intention that leads individuals to prefer electric rather than traditional vehicles. This paper challenges this assumption, and argues that technology frameworks may require new variables to capture acceptance and use of technology. Hence, a UTAUT2-based study has been developed to assess the role of environmental concern in the BEVs context, and put forward the concept of technology show-off (TS) to explain acceptance of the technology.

Design: A quantitative and cross-sectional look at the behavioral intention is adopted. The study uses structural equation modeling to analyzes a sample of 236 Macau residents to determine the relevance of the factors behind the intention to adopt BEVs.

Findings: The result suggests that environmental concern might not be relevant to explain the intention in the BEVs domain, and validates the role of technology show-off as an original measure to explain technology acceptance.

Social implications: To promote the desired behavioral change of BEVs adoption, environmental concern seems to fail in building an argument for the shift to full electric mobility. Herein lies the necessity to take into consideration new variables that can better describe the characteristics of modern society.

Originality: This paper put forward the construct of Technology Show-off (TS) as a significant determinant of behavioral intention to use a technology. TS describes the extent to which a technology exhibits the characteristics of visibility and trialability, such that the higher the measurement, the stronger the behavioral intention to adopt the technology. Also, the paper stresses the need to reconsider the role of environmental concern in technology research.

Keywords: Technology Show-off, Environmental Concern, Technology acceptance, Battery Electric Vehicles, UTAUT2, Consumer Behavior.

1. Introduction

The awareness regarding the detrimental effects of human actions on the environment has grown over the years, with air and water pollution typically at the top (Nielsen, 2018), pushing consumers to make adjustments in their shopping habits (Silva et al, 2021; De Canio et al. 2021). Individuals who are concerned with the environment tend to reduce the consumption of goods that are perceived to have a significant ecological impact (Kropfeld et al., 2018). Also, consumers are more likely to adopt environmentally friendly behaviors as their environmental concerns grow stronger (Nielsen, 2018), which typically also includes the adoption of electric vehicles (Hamzah & Tanwir, 2021). Many studies have demonstrated the correlation between environmental concern and the adoption of eco-friendly vehicles (Singh, Singh & Vaibhav, 2020), thereby considering environmental concern as the primary factor for deciding to use BEVs (Rezvani et al., 2015). Indeed, the electrification of transportation has long been regarded as a promising technology leading to pollutants reduction and preserve the environment (Zhao et al., 2021). For a small territory like Macau, the issue of electric mobility is particularly relevant because ground-level ozone (O_3) is a major pollutant in the region (Wong, 2018). Indeed, the IQAir report (2020) ranks Macau as one of the most polluted countries in Southeast Asia. It is not surprising that residents recognize the benefits of reducing pollution, which would not only make them healthier but also enhance Macau's appeal as a tourist destination (Lai et al., 2015, Teixeira & Silva, 2019). Despite the Chinese government’s efforts for sustainable transportation (Bohnsack, 2018), the penetration of electric vehicles in Macau is relatively low. For instance, the number of BEVs registered in 2020 totaled 980 units (DSEC, 2022), compared to more than 111,000 vehicles registrations in that same year.

The high purchase price and the limited driving range are typically identified as barriers to BEVs adoption (Rezvani et al., 2015; Metz, 2019). If we look at vehicle price as one of the key factors, we may find that Macau has great market potential as it is ranked among the wealthiest places in the world (Fraser, 2018). In fact, government statistics shows that residents enjoy an average monthly salary of USD 2,125 (but considerably higher in the Casino sector) and have bank deposits of about USD 125,000 per capita (DSEC, 2020). Also, vehicle taxation in Macau is lower than in other regions, which influences the demand for luxury over non-luxury vehicles (U, 2019). Additionally, the relatively small size of the territory (32,9 Km^2) (DESEC, 2022) seems to be an excellent fit in terms of the driving range of the most common battery electric vehicles (Metz, 2019).
In a territory where the population is generally concerned about the environment, and the typical resistance factors for BEVs adoption do not seem to hold true, there is the need to consider other elements that could affect the intention to adopt battery-electric technology. Thus, some critical questions guiding our investigation emerge: *What factors might explain BEVs adoption in Macau? What is the role of environmental concern in the decision to adopt the technology? What other factors might better explain the peculiarities of consumers?* Finding the answer to these questions would help scholars to deepen the understanding of consumer behavior, and give marketers the tools to devise accurate communication and marketing strategies related to technology adoption in fast developing economies. Therefore, the aim of this paper is twofold: 1) to assess the key factors that impact on the behavioral intention to adopt BEVs in Macau, and 2) to identify original factors capable of explaining consumers' behavior in the technology adoption domain. These objectives are addressed by building on the UTAUT2 (Venkatesh et al. 2012) framework, a synthesis of earlier technology research. Besides assessing the impact of environmental concerns on consumers' intention, we also discuss some of the characteristics of innovations, namely observability and trialability (Rogers, 1983) that could help to explain the peculiarities of our sample.

This article is organized to give readers an idea of Macau's reality, followed by a review of the literature used to inform the study. Finally, discussion, conclusions, and futures research opportunities are presented.

The Context of Macau

Located at the mouth of the Pearl River delta, nearby Hong Kong, Macau became a special administrative region (SAR) in 1999, and part of China. With the Chinese central government concession over casino activities (Sheng & Gu, 2018), the territory has developed into a popular tourist destination in Southeast Asia, with gambling as its main economic driver (Lampo & Lee, 2011). The territory consists of a peninsula and two islands, and has a total population of 679,600 inhabitants in an area of 32.9 km2 (DSEC, 2022). In 2019 (in the pre-COVID economy), the region registered over 39 million visitors, that contributed to a per-capita GDP of MOP 645,438 (ca. US$ 80,800) (DSEC, 2020). The unprecedented wealth has also affected the surge of motor vehicle ownership. In 2020 there were 111,369 vehicles for private use, an average of one car every six inhabitants. (DSEC, 2022). There were 980 full-electric vehicles in Macau in the same year, representing just the 0.88% of all vehicles. Since BEVs have zero gas emissions, their uptake could potentially reduce air pollutants and positively impact people's health and the tourist image of the SAR. Residents would also be able to mitigate some of the negative effects associated to the quality of life in a fast-developing economy (Teixeira & Silva, 2019).

2. Theoretical Background

Over the years technology research has produced different theories to explain why individuals accept innovations. While recognizing the variety of frameworks, this research is grounded in the UTAUT2 (Venkatesh et al., 2012) as a comprehensive synthesis of earlier technology research adapted to a consumer context. The UTAUT2 presents seven constructs (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit) that are expected to influence positively and directly the behavioral intention to use a technology. Based on extensive research (Tamilmani, Rana & Dwivedi, 2020; Tamilmani et al., 2021) these constructs have been used to inform our hypotheses in line with Venkatesh et al. (2012).

The development of the construct put forward in this study (i.e., technology show-off) is drawn from diffusion of innovations (Rogers, 1962). Rogers (1983) argued that the adoption rate of technology innovations could be explained by studying five attributes:

relative advantage, compatibility, complexity, trialability, and observability. Some of these factors have been included and extensively discussed in technology acceptance theories (Venkatesh et al. 2003). For example, complexity has been used in the Model of Personal Computer Utilization (MPCU) (Thompson et al., 1991), relative advantage in innovation diffusion theory (IDT) (Moore & Benbasat 1991), compatibility in the Decomposed Theory of Planned behavior (DTPB) (Taylor & Todd, 1995), and all subsequently streamlined in the original UTAUT (Venkatesh et al. 2003). However, technology adoption research has overlooked the trialability and observability characteristics of innovations. More precisely, Rogers (2003) defined trialability as the degree to which an innovation may be experimented, and visibility as the degree to which the results of an innovation are visible to others. In this study, these characteristics are deemed worth examining since they contribute to decrease the uncertainty of adopting a technology (Rogers, 1983), and are virtually absent in technology acceptance research.

2.1. Concern for the environment

Meta-analysis studies related to the choice of environmentally-friendly vehicles have abundantly shown the link between environmental concern and vehicle adoption (Singh et al., 2020). Literature defines concern for the environment as the degree to which individuals are aware of environmental problems, and are willing to contribute personally to their solution (Dunlap & Jones, 2002). Kropfeld et al. (2018) noticed that environmentally concerned individuals tend to reduce consumption of goods that they believe have a strong ecological impact. As environmental concern increases, individuals show more willingness to change their behavior. For example, strong concern is believed to translate into the adoption of electric vehicles, as they are eco-friendly innovations (Rezvani et al., 2015). Also, individuals in the wealthiest nations tend to possess higher levels of environmental concern (Franzen & Vogl, 2013), which translates into the willingness to pay a premium for electric vehicles (Ng, Law and Zhang, 2018). With the exception of a study (Ivan et al., 2015) describing environmental concern as the initial factor in BEVs choice, the literature in Macau is absent. It is therefore important to assess this factor in the light of the more recent literature, as well as the wealth development of local society.

2.2. Broader Influences on Technology Acceptance

The decision to adopt a technology not only depends on the practical benefits that are satisfied, but also on what the technology represents to the user (Rogers, 2003; Griskevicius, Tybur, & Van den Bergh, 2010). Individuals adopt and display certain goods to enhance their sense of self, portray an image of what they are like, represent what they feel and think, and bring about the types of relationships they wish to have (Eastman & Eastman, 2015). In particular, the intention to adopt BEVs technology fulfills both utilitarian and social purposes (Steg & Gifford, 2005; Ozaki & Sevastyanova, 2011). Innovations spread because the social structure affects their diffusion in several ways (Rogers, 2003). Although the construct of social influence has been captured in the UTAUT2, other aspects related to consumers' interaction with society are still missing. Roger (2003) argued that one of the important motivations to adopt an innovation is the desire to gain social status. While traditional approaches associate status motives with luxury (Vigneron, 1999), research has pointed out that people may choose products because they communicate some types of information to others, and, sometimes, because they are considered to be "cool" (Warren et al, 2019). According to Rege (2008) products can signal non-observable abilities. For instance, an individual may intend to buy a specific car because it functions as an indication of ability, which increases the chances of making connections with high-ability people. Similarly, Griskevicius et al. (2010) showed that people may prefer green vehicles over more luxurious non-green options on the basis of making a statement about their care for the environment. Symbolic meanings are thus essential in adopting a technology such as BEVs, as they relate to consumers' attitudes towards elements other than price, performance, style, and environmental benefits (Rezvani et al., 2015). Hence, adopting BEV might provide a social utility beyond inferences of wealth. As a matter of fact, consumers' choice of products could signal meanings such as users' knowledge, technological skills, openness to experiences, or prosocial behavior (Luomala et al., 2020). These factors are conceptually different from the constructs adopted in mainstream technology acceptance theory. The explanation of these factors become relevant as time goes by, and as digital marketing, social media, as well as environmental concern, become inexorable. As a result, theoretical models need to be updated to incorporate these connotations.

3. Model Development

Preliminary Study

To complement the literature review, a preliminary exploratory study was conducted with three local industry experts in the form of semi-structured individual interviews. Their responses tended to be similar, and deemed sufficient for the purpose of collecting background information. The participants were informed about the UTAUT2 constructs, and invited to comment. They were also encouraged to share their opinion on any other element judged relevant to our context. All the conversations were recorded by using a mobile phone app, subsequently transcribed and organized into broader themes in line with Maxwell (2012). The preliminary analysis supported the use of the model, however it also exposed how the UTAUT2 predictors were not sufficient to explain other factors in technology adoption. In particular concepts related to the growing concern for the environment, and the effects of BEVs adoption within the community, tended to surface frequently in the conversations. Thus, the constructs of environmental concern and in particular of technological show-off were introduced in our research model as described in the following sections.

The UTAUT2 Constructs

Research has extensively supported the use of the UTAUT2 (Venkatesh et. al., 2012) in information systems and beyond. At the time of writing, the paper Venkatesh et al. (2012) has been cited nearly 10,000 times according to Google Scholars (2022). As the extension of the original UTAUT model (Venkatesh et. al., 2003), the UTAUT2 framework consists of seven core constructs, namely performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating condition (FC), hedonic motivation (HM), price value (PV), and habit (HB), that are theorized to have positive and direct effect on the behavioral intention (BI) to use a technology. As a general rule, the stronger each factor with respect to a specific behavior, the stronger an individual's intention to perform that behavior (Venkatesh et al., 2012). In several UTAUT2-based meta-analysis (Tamilmani et al., 2020; Tamilmani et al., 2021) confirmed the relationships in the model. Accordingly, in line with Venkatesh et al. (2012) and the extensive literature, we formulated a first group of seven hypotheses (H1 to H7) as it is expected that the UTAUT2 constructs (PE, EE, SI, FC, HM, PV, and HB) will have a significant and positive effect on behavioral intention to use BEVs. Two additional hypotheses were formulated as discussed further.

Environmental Concern

Studies related to the purchase of environmentally-friendly vehicles have largely confirmed the link between environmental concern and vehicle choice (Singh et al., 2020). In a study grounded on the UTAUT2, Yoo et al. (2015), found that environmental concern plays a key role in the decision to adopt a technology. Similarly, Riga (2015) found that EC impacted on the behavioral intention to adopt hybrid vehicles technology, and suggested using the construct as an independent variable in the UTAUT model. Additionally, the literature and the interviews with key informants also suggested that Macau residents are typically highly concerned with the environment. Hence, the construct of environment concern (EC) was introduced in the research model. In line with previous studies, it is expected that the individual perception of EC is a key determinant of behavioral intention, such as the higher the measurement, the stronger the behavioral intention to adopt the technology. Therefore, our hypothesis H8 stated that *Environmental Concern (EC) has a significant and positive effect on the behavioral intention (BI) to use BEV.*

Technology show-off

The notion of technology show-off (TS) is put forward as an original construct inspired by the diffusion of innovations theory (Rogers, 1983; Moore & Benbasat, 1991) and adapted to our context. Although some of Roger's (1983) attributes of innovations have been integrated into different models, the characteristics of trialability and observability have been left behind in research.

Using Hurt and Hubbard (1987) argument that observability and trialability could be treated as a single concept (and yet not considered in research), this paper proposes a new a new factor to assess the extent to which a technology is visible and accessible before deciding on its adoption. The term *technology show-off* was developed after informants used “show off” to describe how BEVs technology displays its features (of visibility and trialability) in the society. This study thus expects that the more visible and available for tryout a technology is perceived by the individuals of a society, the stronger the behavioral intention to adopt it. This seems to be specifically relevant to a society that favors products with high social desirability. Therefore, our hypothesis H9 stating that *Technology Show-off (TS) has a significant and positive effect on behavioral intention to use BEV* was formulated.

Hypotheses summary and Research Model

Our study proposes nine hypotheses; seven were adopted from the UTAUT2, while the development of the model (as discussed earlier) led to additional two hypotheses related to the constructs of environmental concern (EC) and technology show-off (TS). The following Table 1 presents our hypotheses.

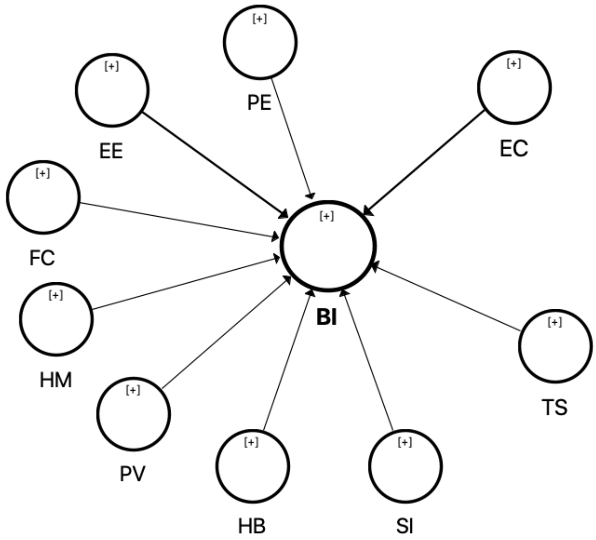
Table 1: Summary of hypotheses

H1	PE has a significant and positive effect on behavioral intention to use BEV.
H2	EE has a significant and positive effect on behavioral intention to use BEV.
H3	SI has a significant and positive effect on behavioral intention to use BEV.
H4	FC has a significant and positive effect on behavioral intention to use BEV.
H5	HM has a significant and positive effect on behavioral intention to use BEV.
H6	PV has a significant and positive effect on behavioral intention to use BEV.
H7	HB has a significant and positive effect on behavioral intention to use BEV.
H8	EC has a significant and positive effect on the behavioral intention to use BEV.
H9	TS has a significant and positive effect on behavioral intention to use BEV.

Authors' elaboration: performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating condition (FC), hedonic motivation (HM), price value (PV), habit (HB), Environmental Concern (EC), Technology Show-off (TS).

Based on theory, the indicators of eight constructs (PE, EE, SI, FC, HM, PV, HB, and EC) are modeled as reflective. Technology show-off (TS), however, is modeled as formative since it represents the synthesis of two different indicators (i.e., observability and trialability) in line with Hurt and Hubbard (1987). Figure 1 outlines the research model, and Table 2 illustrates the summary of the constructs.

Figure 1: Theoretical Framework



Source: Proposed model to explain Behavioral Intention to adopt BEV

Table 2: Summary of the constructs

Construct	Abbreviation	Items	Reference	Construct
Behavior Intention	BI	3	Venkatesh et al. (2012).	Reflective
Performance Expectancy	PE	3		Reflective
Effort Expectancy	EE	4		Reflective
Social Influence	SI	3		Reflective
Facilitating Conditions	FC	4		Reflective
Hedonic Motivation	HM	3		Reflective
Price Value	PV	3		Reflective
Habit	HB	3		Reflective
Environmental Concern	EC	6	Kilbourne et al. (2008).	Reflective
Technology Show-off	TS	2	Hurt & Hubbard (1987); Moore & Benbasat (1991).	Formative

Source: own elaboration.

4. Research Design

Our main approach was descriptive, and intended as a cross-sectional look at the behavioral intention to adopt BEV technology assessed by self-administrated surveys.

The Survey Instrument

The questionnaire was based on items adapted from the UTAUT2 (Venkatesh et al. 2012), Kilbourne et al. (2008) and Moore and Benbasat (1991). One adjustment was related to the wording. For example, the original sentence "Mobile internet is reasonably priced" (Venkatesh et al. 2012: 178) was changed into "BEV are reasonably priced." As some constructs reflected the results of prior experiences, the items were adapted to capture respondents' expectations (rather than their experience) about the technology. For example, the original item "I find mobile internet useful in my daily life" was changed into "I find BEV *would be* useful in my daily life". To facilitate the understanding of the questions and encourage participation, the items were translated into traditional Chinese using the back-translation technique (Bhalla & Lin, 1987) to secure construct equivalence. The questionnaire opened with a screening question followed by thirty-four items grouped according to their latent variables. All items were assessed with a 7-point Likert scale with anchors from 1 (strongly disagree) to 7 (strongly agree). The following Table 2 summarizes the theoretical constructs and the associated items.

Table 2: Summary of the constructs

Performance Expectancy (PE)	
PE1	I find BEVs would be useful in my daily life
PE2	Using BEVs would help me moving efficiently
PE3	Using BEVs would make my life easier
Effort Expectancy (EE)	
EE1	Learning how to operate a BEV would be easy for me
EE2	I expect my interaction with the functions of a BEV would be clear and understandable
EE3	I expect BEVs would be easy to use
EE4	I expect it would be easy for me to become skillful at driving BEVs
Social Influence (SI)	
SI1	People who are important to me would think that I should use a BEV
SI2	People who influence my behavior would think I should use a BEV
SI3	People whose opinion I value would prefer I use a BEV
Hedonic Motivation (HM)	
HM1	Driving a BEV would be fun
HM2	Driving a BEV would be enjoyable
HM3	Driving a BEV would be very entertaining
Facilitating Conditions (FC)	
FC1	I have the resource necessary to use a BEV
FC2	I have the knowledge necessary to decide on the purchase of a BEV
FC3	Battery electric technology is compatible with other technologies I use
FC4	I can get assistance if I have problems using a BEV
Price Value (PV)	
PV1	BEVs are reasonably priced
PV2	A BEV is a good value for money

PV3	At the current price, BEVs provide a good value
Habit (HB)	
HB1	The use of BEVs could become a habit for me
HB2	I could become dependent on using BEVs
HB3	I feel I must use a BEV
Behavioral Intention (BI)	
BI1	I intend to use a BEV in the future
BI2	I predict that I would use a BEV
BI3	I plan to use a BEV soon
Environmental Concern (EC)	
EC1	I am very concerned about the environment
EC2	Humans are severely abusing the environment
EC3	I would be willing to reduce my consumption to help protect the environment
EC4	Major political change is necessary to protect the natural environment
EC5	Major social changes are necessary to protect the natural environment
EC6	Anti-pollution laws should be enforced more strongly
Technology Show-off (TS)	
TS1	I have many opportunities to see BEVs in Macau
TS2	I have had many opportunities to try a BEV in Macau

Source: Own elaboration.

The Sample

For the purpose of gathering insights in a shorter period of time, and taking into account the available resources, the study adopted a convenience sampling technique assuming that the respondents were similar to the target population (Hair et al., 2008). Additionally, participants were recruited using the snowball (Flick, 2009) method to reach more subjects for the study. To determine the minimum sample size, researchers (Field, 2011; Hair et al., 2022) recommend between 10 to 15 observations for each predictor in the model, or the use programs such as G*Power (Erdfelder, Faul, & Buchner, 1996). In case of the latter, and considering multiple regressions (.15 effect size, .05 probability error, and .80 power, and nine predictors in the model), G*Power estimated a minimum sample size of 114 cases. It was then decided to double this value, and our fieldwork returned a total of 236 usable responses.

Pilot Test

Recognizing that the design of a sound instrument is essential to collect usable data, a pilot test was conducted to identify potential issues before launching the final survey. According to Shukla (2008), researchers recommend a pilot test sample anywhere between 15 and 30 responses. Hence, we distributed the survey among 24 university students and staff of an academic institution in Macau. While it is acknowledged that data from a student sample may not be representative of the real situation, this approach was relatively convenient as the main purpose was to explore clarity and potential ambiguity of the questions, rather than the generalizability of the findings. After addressing the recommendation to clarify the meaning of one word in Chinese, the survey was deemed ready for full implementation.

Fieldwork

A commercial online platform was used to administer the surveys. The responses were collected using tablets, then automatically uploaded and stored on the platform. Potential respondents were intercepted by the researchers in the proximity of public car parks in major residential and commercial areas in Macau. Participation was voluntary, and no remuneration was offered. The responses were downloaded at once for further processing.

4. Data Analysis and Results

Approach to Data Analysis

This study utilized SmartPLS 3 to perform the data analysis in line with Venkatesh et al. (2003) and Venkatesh et al. (2012), which used the capabilities of SmartPLS for their research. In addition to recommend PLS-SEM to assess constructs with a limited number of indicators (in our model the construct of technology show-off consists of 2 items), Hair et al. (2022) observed that researchers should prefer PLS-SEM over CB-SEM when prediction and theory development are part of the study, as in our case. Before running the PLS algorithm, possible issues with the data (e.g., missing data, outliers, non-normality, and multicollinearity) were assessed and found not to be a source of concern. Additionally, the assessment of VIF values, as in Kock (2015), excluded common method bias.

Assessment of PLS-SEM Results

Our initial evaluation showed that the model satisfactorily explained 57.8% (R^2= 0.578) of the variance of the endogenous variable BI. However, to evaluate a PLS-SEM model adequately, Sarstedt et al. (2017) recommended completing a two stages-process that examines the measurement model (outer model) and the structural model (inner model). As reflective and formative measurements were adopted, the analysis of the measurement model had to be carried out separately (Sarstedt et al., 2017).

Reflective Measurement Model Assessment

Our examination found that the constructs PE, EE, SI, FC, PV, HM, HB, and EC met the relevant assessment criteria. More specifically, all the outer loadings were above 0.70 (Sarstedt et al., 2017), showing that the indicators exhibited a sufficient level of reliability. Further, all AVE values were above 0.50 (Hair et al., 2016), supporting the measures' convergent validity. Composite reliability had values of 0.856 and higher, which is above the conventional threshold of 0.70 (Sarstedt et al., 2017). The Cronbach's alpha values ranged between 0.747 and 0.930, above the 0.70 thresholds (Sarstedt et al., 2017), and all ρA values met the 0.70 thresholds (Hair et al., 2019) as the assessment returned values of 0.748 and higher. These results suggested that the measures of the predictors had sufficient levels of internal consistency and reliability. The following table 3 summarizes the measurements.

Table 3: Construct's reliability and validity

Construct	Item	Loadings	Cronbach Alpha	rho_A	Composite Reliability	AVE
Behavior Intention	BI1	0.763	0.747	0.748	0.856	0.666
	BI2	0.809				
	BI3	0.872				
Performance Expectancy	PE1	0.902	0.786	0.938	0.866	0.684
	PE2	0.759				
	PE3	0.814				
Effort Expectancy	EE1	0.782	0.848	0.900	0.893	0.679
	EE2	0.900				
	EE3	0.855				
	EE4	0.843				
Facilitating Conditions	FC1	0.857	0.864	0.881	0.906	0.708
	FC2	0.841				
	FC3	0.866				

	FC4	0.800				
Social Influence	SI1	0.964	0.932	0.934	0.954	0.873
	SI2	0.914				
	SI3	0.924				
Price Value	PV1	0.867	0.834	0.836	0.900	0.751
	PV2	0.863				
	PV3	0.870				
Hedonic Motivation	HM1	0.891	0.883	0.928	0.925	0.805
	HM2	0.899				
	HM3	0.902				
Habit	HB1	0.868	0.853	0.873	0.910	0.772
	HB2	0.849				
	HB3	0.918				

Source: Author's own table based on Hair et al. (2022). Evaluation criteria: Loadings >0.70; Cronbach's alfa: >0.70; Rho_A: >0.70; Composite reliability (CR): >0.70; AVE: >0.50.

Lastly, discriminant validity was assessed by using the heterotrait-monotrait (HTMT) ratio of correlations, which according to Hair et al. (2022) is the preferred method over the Fornell-Larcker criterion or the assessment of cross-loadings. All the results were below the conservative threshold of 0.85 (Henseler et al., 2015). It was therefore concluded that the constructs were significantly different from each other. The following Table 4 reports the HTMT values.

Table 4: Heterotrait-monotrait (HTMT) ratios

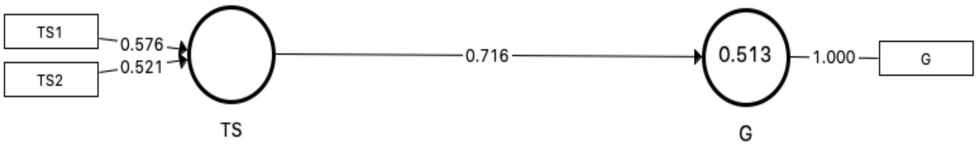
	BI	EC	EE	FC	HB	HM	PE	PV	SI
BI									
EC	0.243								
EE	0.360	0.054							
FC	0.537	0.087	0.272						
HB	0.616	0.133	0.392	0.212					
HM	0.454	0.050	0.136	0.483	0.235				
PE	0.374	0.294	0.160	0.197	0.219	0.103			
PV	0.205	0.263	0.057	0.451	0.146	0.157	0.615		
SI	0.146	0.125	0.118	0.046	0.236	0.169	0.241	0.174	-

Source: Author's own table based on Hair et al. (2022). Evaluating Criterion: HTMT<0.85.

Formative Measurement Model Assessment

The formative measurement model assessment initially focused on the convergent validity by conducting a redundancy analysis of the construct technology show-off (TS). Sarstedt et al. (2017) proposed that redundancy analysis draws on a single global item that approximately summarizes what the construct intends to measure. Therefore, a single item for the construct TS, named G as “Global”, was included in the survey instrument. Accordingly, respondents had to answer the additional statement, "It is easy for me to experience BEV in Macau," which resembled the essence of TS and was used to validate the formative construct following Sarstedt et al. (2017). A new PLS path was therefore created to predict the global measure. The resulting path relationship was above the critical value of 0.70 (Sarstedt et al., 2017), and therefore it was concluded that convergent validity of the formative TS construct was established. Next, it was assessed whether critical levels of collinearity substantially affected the formative indicator weight estimates by examining the variance inflate factor (VIF) values. SmartPLS returned VIF values below the most conservative threshold of 3 (Sarstedt et al., 2017), suggesting that collinearity did not reach critical levels. Testing the indicators' significance implied running the bootstrapping routine. The indicators exhibited statistically significant loadings above the 0.50 threshold, supporting their contribution to the construct TS (see figure 2 and table 5).

***Figure 2: Redundancy analysis**.*



Source: SmartPLS output.; Evaluating criteria: weight>0.50; path relationship >0.70 (Sarstedt et al., 2017).

Table 5: Formative indicator weights and significance testing results.

Formative Construct	Formative Indicator	Outer weights	95% BCa Confidence Interval	t-value	Significant
	TS1	0.576	[0.400, 0.721]	4.295	Yes

Technology	TS2	0.521	[0.366, 0.681]	4.091	Yes

Source: Own elaboration; Evaluating criterion: weight>0.50 (Sarstedt et al., 2017)

The reflective and formative assessment suggested that all constructs presented satisfactory levels of reliability and validity. Therefore, it could be possible to proceed with the assessment of the structural model, discussed next.

Structural Model Assessment

To establish that collinearity issues did not bias the regression results, the VIF values of the constructs were assessed. Most of the values resulted below the more conservative value of 3 (Sarstedt et al., 2017) except five indicators, the highest of which reported a value of 4.231, yet below the threshold of 5 (Hair et al., 2019). Concerning the target-dependent variable BI, it was found that the model explained 57.8% of the construct variance (R^2=0.578), thus exhibiting a moderate to substantial explanatory power (Sarstedt et al., 2017). The examination of the structural paths showed that FC (β=0.301), TS (β=0.269), and HB (β=0.236) had the strongest effect on BI, followed by HM (β= 0.196), PV (β=0.149), PE (β= 0.147), SI (β=0.143), EC (β=0.046), and EE (β=0.025). Bootstrapping results substantiated that, except for the constructs EC and EE, the effects on the endogenous variable BI were significant at the 5% level.

Additionally, the f^2 effect size was assessed to evaluate whether an omitted construct had substantive impact on the target variable. With the exception of EC and EE (that our structural assessment already found not significant) the constructs exhibited some kind of effect. More precisely, small to medium effect was reported for the relationships FC→BI (0.129) and TS→BI (0.125), thus indicating that these relationships had an impact on behavioral intention. All the other f^2 effect sizes were weak and, if below 0.02, could be considered negligible (Cohen, 1988). Although this result is not surprising for the UTATU2 predictors (Tamilmani et al., 2021), it is relevant in case of TS, which is the construct we put forth in this study.

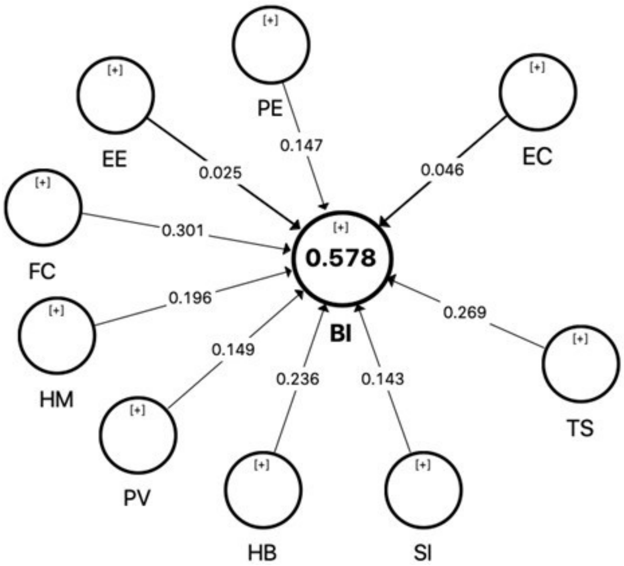
Table 6: f^2 Effect Sizes on BI.

FC	TS	HB	HM	SI	PV	PE	EC	EE

0.129	0.125	0.082	0.070	0.040	0.033	0.036	0.004	0.001

Source: Author's own table; Evaluating Criterion: effect sizes 0.02 (small), 0.15 (medium), 0.35 (large). Cohen, (1988).

Figure 3: Model Estimation



Source: Own elaboration

Measures of Model Fit

A standard measure of quality fit in PLS-SEM is the standardized root mean square residual (SRMR) (Garson, 2016). Our model reported an SRMR value of 0.65, below the conservative 0.80 thresholds (Hair et al., 2017). Also, a complete bootstrapping procedure was initiated (settings: 5,000 samples, BCa bootstrap confidence intervals, two-tailed testing, and 0.05 significance level corresponding to a 95% confidence interval) to obtain the confidence intervals of the index. In our model, the upper bound of the confidence interval was greater than the index, and therefore model fit was positively assessed (Table 6).

Table 6: Indices of model fit.

Index	Saturated Model	Estimated Model
SRMR	0.062 [0.056;0.099]	0.062 [0.052;0.100]

Source: Own elaboration; Evaluating Criteria: SRMR <0.80 (Hair et al., 2017).

Assessment of the Model's Predictive Power

For a PLS path model to be useful, it needs to produce generalizable findings (Hair et al., 2022); this requires assessing the model on the grounds of holdout samples (Sarstedt et al., 2017), that is data that has not been used in fitting the model. In our approach, we used the $PLS_{predict}$ routine based on Shmueli et al. (2016). All indicators in the PLS-SEM analysis had lower RMSE values compared to a linear regression benchmark (LM), thus indicating that the model exhibited high predictive power (Hair et al., 2022). Also, the Q^2 predicted value was larger than 0 (Q^2= 0.534) and approximated the coefficient of determination R^2 (0.578), which also indicated a satisfactory predictive power of the model in line with Hair et al. (2022).

Table 7: Predictive Performance of the PLS Model Versus Linear Model.

Composite	Indicator	PLS-SEM RMSE	LM RMSE	LM-PLS	Q^2 Predict	R^2
Behavior Intention	BI1	0.938	0.954	0.016	0.534	0.578
	BI2	1.343	1.352	0.009		
	BI3	1.051	1.116	0.065		

Source: Author's own table; Evaluating criterion: Q^2 Predict >0 (Hair et al. 2022).

Assessment of Hypothesis

Out of the nine proposed hypotheses, seven were supported; their path relationships were significant at the 0.05 level, had signs in the expected directions with path coefficients (β) ranging from 0.143 to 0.301. Effort expectancy (EE) and environmental concern (EC) were found non-significant, and the associated hypotheses H2 and H8 were rejected. More importantly, the parameters of the construct technology show-off (TS) (β=0.269, p<0.001) confirmed the expected relationship with behavioral intention, and revealed to be a significant contribution to the model. The following Table 8 summarizes the results.

Table 8: Assessment of hypotheses.

Hypothesis	Path	Coefficient	t-Value	*p*-Value	Supported
H1	PE→BI	0.147	2.741	0.006	YES

H2	EE→BI	0.025	0.557	0.578	**NO**
H3	FC→BI	0.301	5.501	0.000	YES
H4	SI→BI	0.143	2.269	0.024	YES
H5	PV→BI	0.149	2.773	0.006	YES
H6	HM→BI	0.196	4.124	0.000	YES
H7	HB→BI	0.236	3.985	0.000	YES
H8	EC→BI	0.046	1.067	0.287	**NO**
H9	TS→BI	0.269	4.954	0.000	YES

Source: Author's own table; Evaluation criteria: t-value>1.96; p-value<0.05.

6. Discussion

Our research adopted the UTAUT2 framework to explore the factors influencing BEV technology acceptance in a sample of 236 Macau residents. While doing so, we expanded upon the traditional theory and focused on environmental concern and the impact of technology show-off on intention. The assessment resulted in a model built around nine hypotheses, of which seven were supported.

Performance expectancy (PE), which relates to the degree to which using a technology will provide benefits in performing certain activities, was positively correlated to the behavioral intention to use the BEVs. Prior studies reported PE as the strongest determinant of intention in most contexts and situations (Venkatesh et al., 2012). In hybrid electric technology, however, the construct was found particularly weak (Riga, 2015) or not significant (Keeton, 2008; Preston, 2016). In our model, although the construct was supported, PE emerged as the weakest contributor. Thus, the construct results particularly weak when trying to explain why people choose to use BEVs for activities that are similar to those performed with traditional vehicles.

Effort expectancy (EE) is linked to the perception of efforts required to use BEVs, and in our context was not significant. A small number of studies related to electric vehicles also produced similar results (Yoo et al., 2015; Madigan et al., 2015). Venkatesh et al. (2003) and Venkatesh et al. (2012) noted that users' experience moderates the construct of effort expectancy, as a result the effect is more substantial in case of limited experience. Therefore, the effect effort expectancy appears to be relevant only during the initial stage of technology use, while it becomes non-significant over time due to experience. In our case, a possible explanation is that drivers to not expect BEVs to be substantially different from traditional vehicles, so that their previous experience can be effortlessly transferred to the new technology.

Facilitating conditions (FC) is related to the respondents' perception of having all the resources that are necessary to decide whether to use BEVs. The relevance of the construct is recognized in several studies in the EV domain (Riga, 2015; Nordhoff et al., 2019; Khazaei & Khazaei, 2019), and our findings are in the same direction. Facilitating conditions resulted the most significant determinant of behavioral intention among the UTAUT constructs. Our findings suggested that residents perceive to possess the resources (e.g., financial means, knowledge, lifestyle) needed to decide to use BEVs.

Social influence (SI) depended on whether significant others (e.g., family, friends, colleagues) think that the respondent should drive BEVs. Our finding is somehow different from the prevailing theory supporting the role of social influence as the major determinant of behavior (Venkatesh et al., 2012; Madigan et al., 2017; Nordhoff et al., 2019). In our sample, social influence resulted in the least significant factor, pointing out that others predictors do a better job in explaining technology acceptance (e.g., FC, TC, HB). Since many people have not adopted BEVs technology yet, it might not be easy to convince relatives or friends to use it as well, thus a relative weak construct was found as a result.

Hedonic motivation (HM) refers to the idea that respondents may find BEVs particularly enjoyable to drive, for example, due to the fast acceleration. Venkatesh et al. (2012) found hedonic motivation to be a critical determinant of behavioral intention and one of the most important drivers in consumer contexts. As a matter of fact, research on EVs has reported this construct among the strongest predictors (Madigan et al., 2017; Aliyev et al., 2019). In our sample, however, other factors do a better job explaining the behavioral intention to use BEVs, such as facilitating conditions, habit and technology show-off.

Price Value (PV) refers to the perception that BEV technology represents a good value for the consumer. Several studies have supported the construct as a determinant in the intention to adopt electric vehicles (Aliyev et al., 2019; Bullard, 2019; Khazaei, 2019), findings that are consistent with our results. Our analysis indicated that the respondents perceived that the BEVs technology had room for improvement at the current price. As a matter of fact, BEV technology is still expensive, a Tesla Model 3 Long Range, for example, is sold at the time of writing at MOP 405,000 (ca. USD 50,400) in Macau (Tesla, 2022), that is price intended to a segment of wealthy technology-driven customers. This may suggest that current owners consider the features and benefits of BEVs much the same as conventional luxury vehicles, and their incomes allow them to be early adopters of this technology.

Habit (HB) is related to the respondents' perception of whether using the technology could become routine behavior. Our analysis revealed this construct to be one of the most substantial factors in the model. This result was particularly interesting because habit has often been excluded from research for the reason that sufficient time had not passed for respondents to form a routine about a behavior (Rana & Dwivedi, 2018). Interestingly, our results endorsed the applicability of the construct in future research models, suggesting also that Macau residents perceived that the use of BEV could easily become part of their everyday life.

Environmental concern (EC) is related to the awareness of problems regarding the environment, thus, individuals with greater concern for the environment are expected to show stronger behavioral intention to adopt BEVs technology (Rezvani et al., 2015; Hamzah & Tanwir, 2021). Surprisingly, our result was different from mainstream research, and the environmental construct resulted non-significant in our context indicating that the choice of BEVs was independent from the environmental concern level of the participants. Indeed, the analysis of the construct showed that the respondents exhibited high concern for issues related to the environment. A possible explanation is that when it comes to motor vehicles, for average consumers, the environmental benefit of the vehicle might be something nice to have, but not the primary reason for choosing the car. Our study suggested that individuals may prefer electric vehicles for reasons other than the environment, for example, we propose, because of the characteristics of a technology to be visible and experimented.

In line with Rogers (1983) observing that the visibility of the results and the possibility to experiment with the innovation are important parts of the adoption process because they help decreasing uncertainty, we put forward the construct of **Technology Show-off** (TS). This factor was intended to describe with a single measure the extent to which an innovation exhibits (i.e., shows-off) its characteristics of visibility and trialability, such that the higher the measurement, the stronger the behavioral intention to adopt the technology would be. With a few exceptions, visibility and trialability have been overshadowed by other constructs in technology research. In a study of information and communication technologies, Usluel, Aşkar, and Bas (2008) supported observability and trialability (although as separate constructs) to explain technology use. In our study, TS resulted in one of the strongest determinants of behavioral intention, and the analysis also validated the suitability of the formative construct as a promising predictor and complement to the UTAUT2 model.

Our result indicated that Macau residents had a positive perception of BEVs technology, perhaps because they were able to see it and experiment it within the territory. Although BEVs for private use are not common, a possible explanation is that residents gained relevant experience also by using public taxi service. As a matter of fact, a fleet of full-electric taxis from Chinese manufacturer BYD started operations in early 2018 (Hua, 2018), thus possibly positively influencing the passengers' perception towards this technology.

7. Conclusion

This study has addressed the factors that determine the intention to accept battery electric technology, suggested the need to reconsider the role of environmental concern in the decision to adopt BEVs, and put forward to construct of technology showoff as determinant of behavior. The findings provided general support for using the UTAUT2 to explain and predict intention in the BEV domain. With the exception of effort expectancy, the core UTAUT2 predictors have performed well in our sample. Therefore, studies about acceptance of technologies that are not in their introductory stage, may want to omit effort expectancy from the model, as the effects of this construct appear to become insignificant over time due to individual experience. Facilitating conditions, in particular, emerged as the most significant determinant of behavior in the UTAUT2. Indeed, our finding indicated that residents perceive to have the necessary condition (e.g., financial means) to make an informed decision on the adoption of BEV technology. Therefore, a relatively fast uptake might be expected within the segment of wealthy technology-driven customers as their incomes allow them to be early adopters of this technology.

Interestingly, environmental concern resulted non-significant in relation to the decision to accept BEV technology. This study revealed that participants were concerned for issues related to the environment, regardless of whether they intended to adopt the technology. This finding suggests the need to reconsider the role of environmental concern as a key determinant of behavior, as our analysis implies that BEVs may be chosen for reasons other than the care for environment. Therefore, researchers may want to look at environmental concern as a background factor rather than a direct predictor of behavioral intention. In fact, in our model other variables did a better job in predicting technology acceptance, such as technology show-off. Indeed, our study proposes the construct of technology show-off to explain the characteristics of the sample; a new theoretical factor that blends the observability and trialability characteristic of innovations into a single formative construct. Technology show-off resulted a key determinant for BEVs adoption in our model. The scales have performed as expected during the assessment, with the construct being able capture and explain part of the peculiarities of our sample. On these premises, it could be expected that a technology that scores higher in this factor might be perceived better than one that scores lower, and consequently more likely to spread faster in the society. This principle may be generally extendable to other technologies and contexts. For example, TS may help researcher predict or explain the popularity of technology products such as the iPhone, which in 2018 held 73% of the smartphone market in Macau (Wong, 2019). Indeed, the phone is highly visible (e.g., family members, classmates, friends, colleagues) and is highly experientable before adoption (e.g., the phone can be freely tested in all major technology stores). Also, the TS construct may be applied to study intention of technology usage in any context where people emphasize being associated with particular group membership and may wish to appear successful in the eyes of their peers. The managerial implications are therefore apparent; shows or exhibitions featuring sections dedicated to BEVs could offer visitors a chance to see the results and experiment with the technology. Consequently, these events would not only enhance the popularity of the participating brands, but also promote the benefits of BEVs, and increase people's awareness of environmental issues. To conclude, technology show-off is regarded as the major achievement of this work, and a contribution to theory and practice as it has put forward a new construct which incorporates two characteristics of innovations that mainstream research has often overlooked.

Limitations and Future Research

This study has provided insights into the factors affecting the behavioral intention to use battery-electric technology. However, there are limitations. Firstly, the results may not be generalized to countries with different social and economic characteristics. Secondly, the research design used convenience sampling under the assumption that the participating individuals were similar to the overall target population. Third, the timeframe and the resources did not make the execution of a longitudinal study extend the analysis to the actual use of the technology. Therefore, it is recommended that future studies use probability sampling techniques and employ a longitudinal approach to determine how behavioral intention translates into the actual use of technology. Although technology show-off resulted in an important contribution to the model, the construct should be further validated in different contexts, technologies, and cultural settings to understand its impact on behavioral intention. In general, future research that builds on our findings could help explain why some technologies get accepted faster than others.

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