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Electric Vehicles Sustainability and Adoption Factors

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Abstract

Sustainability has an ever-increasing importance in our lives, mainly due to climate changes, finite resources, and a growing population, where each of us is called to make a change. Although climate change is a global phenomenon, our individual choices can make the difference. The transportation sector is one of the largest contributors to global carbon emissions, making the transition toward sustainable mobility a critical priority. The adoption of electric vehicles is widely recognized as a key solution to reduce the environmental impact of transportation. However, their widespread acceptance depends on various technological, behavioral, and economical factors. Within this research we use as an artifact the CO_2 Emission Management Gauge (CEMG) devices to better understand how the manufacturers, with integrated features on vehicles, could significantly enhance sales and drive the movement towards electric vehicle adoption. This study proposes an innovative new theoretical model based on Task-Technology Fit, Technology Acceptance, and the Theory of Planned Behavior to understand the main drivers that may foster electric vehicle adoption, tested in a quantitative study with structural equation modelling (SEM), and conducted in a South European country. Our findings, not without some limitations, reveal that while technological innovations like CEMG provide consumers with valuable transparency regarding emissions, its influence on the intention of adoption is dependent on the attitude towards electric vehicles and subjective norm. Our results also support the influence of task-technology fit on perceived usefulness and perceived ease-of-use, the influence of perceived usefulness on consumer attitude towards electric vehicles, and the influence of perceived ease-of-use on perceived usefulness. A challenge is also presented within our work to expand CEMG usage in the future to more intrinsic urban contexts, combined with smart city algorithms, collecting and proving CO_2 emission information to citizens in locations such as traffic lights, illumination posts, streets, and public areas, allowing the needed information to better manage the city's quality of air and traffic.

Keywords: sustainability; electric vehicle; adoption; CEMG; CO_2 emissions

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1. Introduction

Carbon dioxide (CO_2) is the main greenhouse gas, of which approximately one-fifth is emitted by road transport [1], making transport-emitted CO_2 the major cause of air pollution [2,3]. Reducing CO_2 is considered a key factor in preserving the environment [4]. Electric vehicles (EVs) have increasingly been promoted as a solution to reduce gas emissions and environmental problems [5]. Many governments all over the world are implementing policies, or have done so in the recent past, to encourage the production and acquisition of alternative fuel vehicles. Instead of relying solely on fossil fuels, alternative sources are increasingly being used, such as electricity for EVs or bioethanol and biogas for flex-fuel vehicles, both offering promises on future transport development [6]. The market share of these types of vehicles has been significantly increasing in the last years, especially in developed countries such as the United States, where this type of vehicle increased more than 9% from 1.53 million in 2022 to 1.7 million in 2023 [7].

The combination of multiple factors, such as the incentives to acquire electric vehicles, strong worldwide competition between manufacturers, and strong environmental and sustainability concerns, is fostering the need to better understand how companies and vehicle manufacturers can leverage sales and drive adoption, now more than ever. In 2023, the estimated worldwide number of electric vehicles on your roads was 41 million, an impressive increase of 51.8% compared with the previous year when the number was 27 million [8]. Projections point out that this number could scale up to more than 439.2 million by 2035, representing 42.5% of the worldwide vehicle account [9]. Although some electric vehicles' research can be found in literature, at individual and firm levels, and in public and social sectors [10–13], there is almost a complete absence of information on how the manufacturers and the private sector can impact or enhance the EV intention of adoption. It becomes visible that it is imperative to better understand and deepen the analysis on different determinants of electric vehicles customer acceptance, better understand the main reasons for customer choice behavior [14], such as triggers of first usage [15], satisfaction perception, and continuance intention factors [16], and overall interaction between each other, how they are measured, and how they are perceived, complementing earlier knowledge and filling a gap in literature on this matter.

Today little or no information about CO_2 vehicle emissions is provided to drivers or vehicle users in the moment or during the period they are using them. Most earlier studies focused on measuring CO_2 at the city, region, or country level [17], but until now almost no studies were made at the individual driver level to capture individual perceptions on the environment and sustainability impact, requiring additional investigation. One of the keys to understanding if sustainability is being achieved is measuring and understanding emissions. Our research will focus on the impact of an innovative CO_2 Emission Management Gauge (CEMG) artefact, as far as we know not yet studied in literature, which can be onboarded on vehicles. Based on Life-Cycle Assessment (LCA) and measuring how much emissions the consumer is emitting when using a determined vehicle, according to the use phase average calculations, it could be a game differentiator, providing real-time emission information [18–21].

One of this study's initial objectives is to provide empirical evidence on the determinants of environmental strategy in the automotive market that are being developed by the vehicle manufacturers and by the private sector. In more detail, the main research objectives are the following: (i) identify and describe the most important sustainability and individual behavior variables from previous literature, (ii) design an innovative and not-yet-tested-in-literature theoretical model based on sustainability, technology, and individual behavior factors, (iii) examine the effects of sustainability features on individual behavior, (iv) identify best practices to follow in the automotive sector, and (v) identify the impact of CEMG on vehicle consumer decision-making.

The paper is structured as follows. We will start with an extensive literature review, focused on exploring earlier studied determinants and classifying them to better understand how they interact with each other and with the private sector measures and how they impact individual behavior on a consumer level. In the following chapter we will present the new and innovative theoretical model designed to support our work and the main hypotheses identified, followed by the methodology, main work results, discussion, and theoretical and practical implications sections. Our work ends with the limitation, future work, and the main conclusion sections.

2. Literature Review

2.1. Electric Vehicles (EVs)

Fossil fuels continue to be the main source of energy production [22]. The year that some predictions assume for the complete depletion of oil resources in the world is 2038 [23]. This date is known to be controversial, since in the past several other dates were identified that turned out to be untrue, but it gives an idea of current oil reserves worldwide. EVs have been largely studied as viable, energy-efficient, and environmentally friendly alternatives [24] to reduce the effects of an oil-centered and heavy-polluting transport market [25,26]. This transition for pro-environmentally focused options is often seen with skepticism by the automotive sector that, until recently, did not provide its consumers with knowledge or experience about EVs as alternatives [12,19,21,27]. Nevertheless, EVs are not new; they have been around for decades. The use of rechargeable batteries as a vehicle power source dates from the 19th century [13,28,29]. Nevertheless, due to non-competitive prices, some mass-production difficulties, and mainly a very strong and aggressive fuel market, they did not become mainstream, and the internal combustion engine (ICE)-oriented vehicles have been indisputably dominating the market [13] until now. Recent advances in automotive electrification have been changing this market landscape by providing new options and ways of commuting and transporting while reducing some of the previous fears and consequences of EV usage [15]. Aside from technical improvements, new architecture solutions implemented enable consumers to better understand and classify the different types of vehicles and associate each of them with necessities of one's routine to assign a better fit for consumer needs [30].

Considering the purpose of our study, vehicles will be separated into three groups, as presented in Table 1; the first will be called non-electric engine vehicles (NEEVs) and will contain vehicles that rely completely on their ICE and encompass both FFVs and fossil combustion vehicles (FCVs; vehicles that rely only on fossil fuels). The second group will be addressed as electric hybrid engine vehicles (EHEVs), grouping vehicles that present an ICE but also an electric drivetrain, representing hybrid electric vehicles (HEVs) and plug-in hybrid electric vehicles (PHEVs). PHEV provides the possibility of recharging the electric drivetrain through the electric grid, allowing them to drive between 30 km and 150 km in a purely electric mode, depending on the vehicle capacity [31]. Some authors consider this a transitional stage in the development of pure electric vehicles, as people become increasingly concerned about the environment [32]. The last group will be named electric battery engine vehicles (EBEVs) and will contain vehicles that do not present an ICE and rely solely on the electric drivetrain that must be charged by the electric grid to be used, which encompasses and defines battery electric vehicles (BEVs) [18,33–35].

Table 1. Vehicle Groups Composition (from the authors), supported in earlier literature [18,33–35].

Vehicle Group	Composition
NEEV	FFV; FCV;
EHEV	HEV; PHEV;
EBEV	BEV;

Legend: NEEV = Non-Electric Engine Vehicle, FFV = Flexfuel Vehicle, FCV = Fossil Combustion Vehicle, EHEV = Electric Hybrid Engine Vehicle, HEV = Hybrid Electric Vehicle, PHEV = Plug-In Hybrid Electric Vehicle, EBEV = Electric Battery Engine Vehicle, BEV = Battery Electric Vehicle.

2.2. Determinants of Adoption

Earlier research on what drives EV adoption is mainly focused on (i) the public and (ii) social sectors, respectively encompassing governments and governmental actions and representing the consumer and its consumption habits. This leaves a certain gap in how the private sector, encompassing the companies and brands, can assess their weight in this equation. It is important to take into consideration that when talking about EV adoption, the intent of adoption of technological innovativeness is what is being measured [36] as the intention to adopt, and actual adoption share the determinants and differ only in prediction assertiveness [13]. The main groups of determinants found in literature are summarized in Table 2 and described in detail in the following sections.

Table 2. Adoption's main groups of determinants (from the authors), supported in earlier literature [11,13,15,35].

Social Sector	Attribute	Factor
Public	Symbolic	Environmental Position
		Support
Social	Symbolic	Environmental Position
		Green self-Identity
		Social Influence
	Instrumental	Ease of Use
		Relative Advantage
		Perceived Risks
	Hedonic	Enjoyment
		Pleasure

2.2.1. Governmental Support and Social Proactivity

Drivers of adoption are not always associated and dependent solely on consumers. Previous literature analyzes and states the importance of public sector support and pro-environmental positions, classifying them as critical to the initial steps of EV adoption. Early-stage governmental incentives such as tax reductions, subsidies, and synergies with the social sector can largely impact consumers' intention of adoption [11,37]. Some leading opinion also rises as a critical point that can be associated with governmental actions, such as regulatory pressure in Germany [15] or fiscal incentives in the UK [38], and are major drivers of adoption [35], as influential leaders can shape social perception [39,40] and facilitate the diffusion of the innovation process in this scenario [41]. Previous research also delves into how strengthening the engagement between interstate institutions that dominate official deliberations would enhance sustainability governance, mainly by regulatory cooperation [42], where international organizations can stimulate and focus public demand while reducing fragmentation by promoting industry-wide standards. This is visible in the United Nations Environment Program (UNEP) engagement with business, which has, aside from many other activities, promoted benchmarked corporate environmental reports and developed sector-specific standards, such as the Finance and Tour Operators Initiatives [43,44].

Public sector incentives have been proven critical for EV acquisition [27], but other variables also weigh in the decision. A proactive and engaged social sector able to generate a demand increase on this market is crucial to progress with transport electrification while synergizing with the previous public sector support and enabling private sector investments to supply such demand [11]. The adoption of EV intersects significantly with the proactive involvement of the social sector, as pointed out in previous literature, to increase demand after public-social dialog has taken place [11]. This involvement may have a multitude of different triggers, and previous research analyzes key points of it by separating these factors into symbolic, instrumental, and hedonic attributes [13].

2.2.2. Symbolic Attributes

Consumers tend to create an individual image of a product based on their own perception. When that image aligns with their self-image/identity, it creates a positive effect on adoption [13]. This perception about EVs can be explained by the Self-image Congruency Theory [45], which posits that consumers that perceive that their self-image matches consistently the product's image are more inclined to present a positive attitude towards it. The environmental position of a consumer is considered a critical determinant in the adoption of electric vehicles, as it can shape the consumer's self-image [15,35] and still be influenced by other sectors with environmental marketing campaigns and other types of public advertising focusing on bridging consumers' intentions and actions [11].

A green self-identity, when congruent with the perceived image of a product, can lead to the strengthening of the consumer's motivation to engage with the product itself and to express its position, identity, and pro-environmental intentions to others [15,46]. This engagement greatly impacts the social influence concept in which, in this scenario, consumers influence and are influenced by each other, by organized groups, and by the private sector, mainly by contagion, dissemination, and translation [35,47]. This positive impact is supported by diffusion of innovation [41] research that takes this engagement on environmental promotion and understands how this personal influence is exerted and how it changes others' opinions and actions by applying the theory of opinion leadership and separating roles of opinion leaders and opinion seekers while understanding their impact on the social network they are inserted in.

2.2.3. Instrumental Attributes

Functionalities and utilities that are presented by a product or technology impact directly and indirectly the way the potential adoption will take place [48]. In the case of EV, empirical evidence from previous literature studies shows the relevance of a few instrumental topics to the adoption and consumption of EV, such as pricing, usage costs, maintenance, performance, range, and infrastructure [38,49]. These instrumental topics can be grouped into another classification consisting of ease of use, relative advantage, and perceived risks to better understand drivers of adoption [15]. With the previous examples provided, classification could be done by grouping performance and range under ease of use, pricing and usage costs under relative advantage, and maintenance and infrastructure under perceived risks. It is imperative to perceive that the topics may fall under other groups depending on the situation and comparison being made, but the instrumental concept of these topics is what needs to be understood.

2.2.4. Hedonic Attributes

Consumer's feelings of variation, pleasure, fun, excitement, and other emotional experiences in their interactions with products or services are a strong driver in the direction of adoption and usage [13,50]. Hedonic attributes refer to the experiential and emotional aspects associated with a product rather than its utilitarian or functional aspects or the symbology consumers feel they need to exert from product usage [15,48].

2.3. Sustainability as a Driver

Governmental incentives for the production and consumption of EVs are a key factor in EV adoption by the social sector and, consequently, in the reduction in CO_2 emissions.

Taking this into consideration, it is of crucial importance to carefully calculate sustainability values, as metrics often consider only tailpipe emissions, which are only one of the considerable aspects raised on EV adoption impacts [51]. The tool that has been constantly implemented by studies when it comes to CO_2 emission measures by transport options has been the Life Cycle Assessment (LCA). LCA revolves around computing production, usage, supply chain, and disposal. It quantifies emissions and resource usage along the product life cycle, measuring them on Global Warming Potential (GWP) calculated on grams of emission of CO_2 per kilometer of usage (eCO_2 g/km) [18]. LCA has been previously used in numerous studies, and its model has been incremented continuously since its conception [52,53]. LCA has been used on the development of new consumption and emissions measuring tools, such as Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET) 1-series [54] and 2-series [55]. The LCA model can become as complex as the extent of the due diligence of processes and suppliers can be assessed, so to reduce system complexity [22], a few negligible items may be excluded from calculations, providing us with the simplified life-cycle structure [18] for the different vehicle groups considered in this study presented in Figure 1.

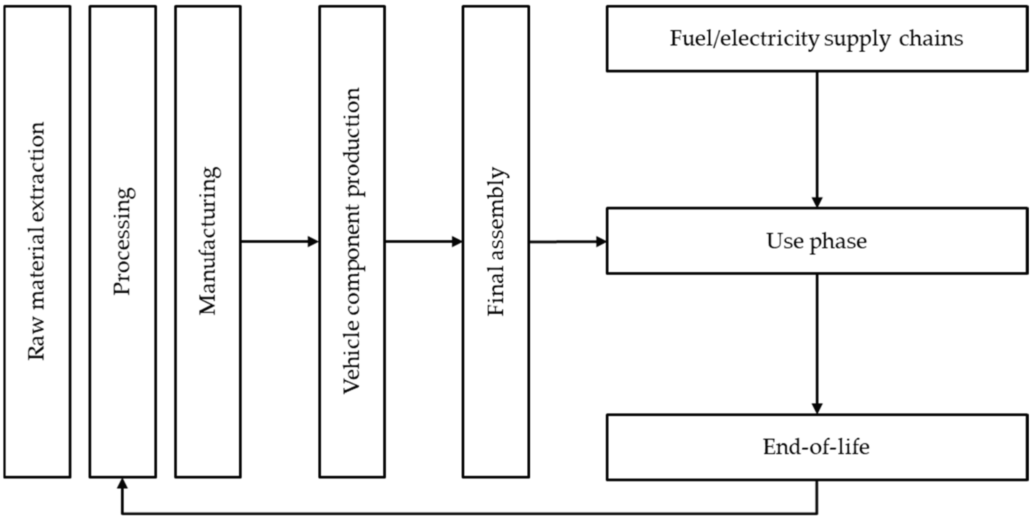

Figure 1. Simplified NEEV, EHEV, and EBEV vehicle life cycle (from the authors), supported in earlier literature [18].

One key aspect that is critical to consider when understanding how NEEV, EHEV, and EBEV vehicles fit into LCA is that the most relevant components of the three mentioned life cycles are rather similar, and what will provide the significant difference in the overall analysis are the values of resource consumption and emission releases on the individual processes and components [18,56].

Earlier literature successfully implemented LCA to better understand the different emission levels on different types of vehicles, including NEEV, EHEV, and EBEV. The results pointed out that when taking into consideration vehicles' life cycle, the emissions from raw material extraction to final assembly are numerically similar, and the fuel supply chain emissions presented on NEEV vehicles are also equivalent to the emissions of battery production on EBEV vehicles [18]. An important topic when understanding the use phase, which consists of analyzing driving and charging patterns, maintenance, and part replacement of EBEV and EHEV vehicles, specifically the PHEV, is that there is a large difference in emission levels regarding the electricity generation technologies, as there is the possibility for the electricity being generated from coal, natural gas, or non-fossil resources that could impact the analysis on the charging pattern aspect. This research will consider the emissions regarding the electrical supply chain as the average value between coal, natural gases, and non-fossil resources.

2.4. Determinants Interaction

Numerous theoretical models, such as the theory of planned behavior (TPB) [57], the value belief norm theory (VBN) [58], the technology acceptance model (TAM) [59], and other models [41,60], have been previously used to try to understand and predict the impact of EV adoption on the automotive market [61–63], where the complexity of adoption and risk perception of customers becomes clear regarding a few common topics such as battery range, higher costs, existing and planned charging infrastructure, and the future of the technology [1,64]. These determinants have been the focus of many studies, and a few of them manage to provide an interconnectable view of how different sectors and attributes influence each other. Previous literature focused on understanding how the public, social, and private sectors can interact with each other in order to foment EV adoption [11]. Evolutionary Game Theory (EGT) [65] proves that the public environmental position and the public support, which is enhanced by the first, cause direct impact on the social symbolic attributes that encompass social environmental position, green self-identity, and social influence. These last three were associated, and their interaction was also previously studied by literature using Value Belief Norm Theory (VBN) [58], which managed to perceive that social green self-identity causes a direct impact on social environmental position and social influence and that the social environmental position is also responsible for mediating these social influence aspects [46]. The three considered attribute aspects (instrumental, symbolic, and hedonic) also had their interaction previously mapped using the Theory of Planned Behavior (TPB) [57], where the instrumental attributes were proven to be mediated by symbolic and hedonic ones on the intention of adoption of EV [13]. Comprehension of how instrumental attributes impact adoption has also been analyzed, and previous research using the Technology Acceptance Model (TAM) [59] managed to associate the impact of ease of use both on perceived risks and perceived relative advantage and how the perceived risks mediate the perceived relative advantage [15]. Regarding the private measures intended to enhance the intention of adoption and actual adoption, the Task-Technology Fit Model (TTF) [60] has been largely used to assess the effectiveness of information systems solutions based on the tasks provided, functionalities, and individual performance, such as creating a comprehensive assessment of the success of the implementation of mobile information systems [66].

3. Research Model

Our theoretical model embraces observability features provided by the private sector and how they drive adoption and tests these improvements in usage against the constructed model. The scope of actions that can be taken by the private sector to increment EV adoption is large, so to be able to extract meaningful value, this study will focus on observability as a feature, mainly looking at the ability to provide the consumer with information about how much the EV is contributing to the reduction in CO_2 and how this feature could influence the social perception of relative advantage and social environmental position by providing a CEMG integrated in the vehicle. Another objective of this study is to try and empirically assess the impact of this possible observability feature provided by manufacturers and understand how the integration of this kind of metric and monitoring can enhance the adoption of EV technology in this ever-changing market.

3.1. Model

Some earlier studies managed to aggregate different models to further understand intention and consumer adoption [67,68]. Our theoretical model integrates the TAM [59], which provides the main body of structure to understand adoption, with TPB's [57] social influencing variables Perceived Behavioral Control and Subjective Norm, and TTF [60], enabling us to further understand how the monitoring features provided by the private sector can impact. By using a combination of these three well-established models, TAM, TPB, and TTF, as the ground force of our study, as presented in Figure 2, we intend to provide substantial improvement in the capacity to explain EV adoption when integrated emission artifacts' or observability features are available.

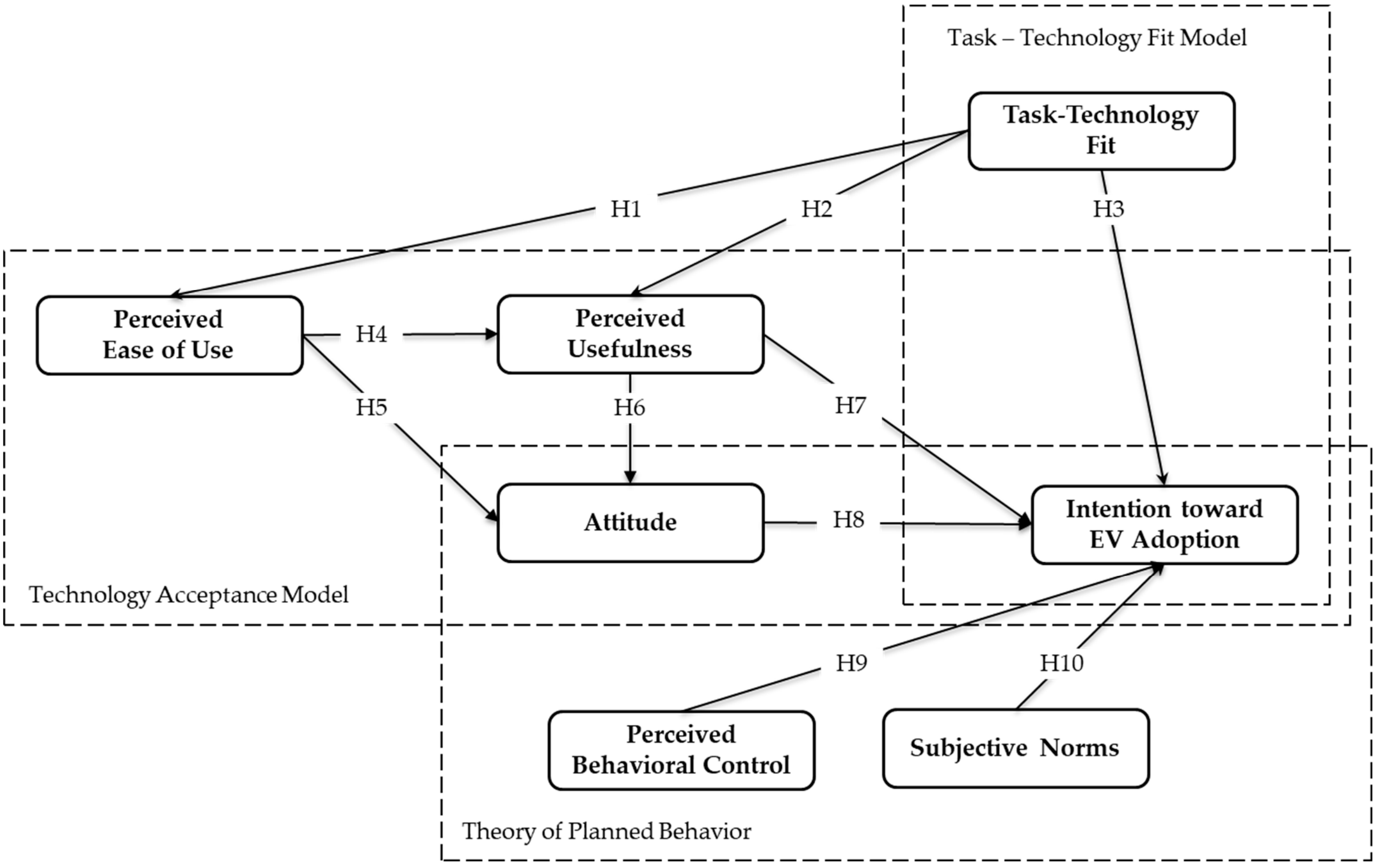

Figure 2. Conceptual model (from the authors), combining the Theory of Planned Behavior [3], Technology Acceptance Model [18], and Task—Technology Fit Model [35].

3.2. Hypotheses

3.2.1. Task-Technology Fit

Task-technology fit provides the rationale for understanding that the feature at hand (CEMG) adds value and is interesting in solving the proposed issue, which is providing the consumer with information regarding how much the usage of EV would be impacting its pro-environmental agenda [16]. The relation between TTF and Perceived Ease of Use works mainly on providing further understanding of the technology capabilities, while the relation of TTF with Perceived Usefulness and Intention of adoption are the actual key components of these model aggregations [60,67]. Therefore, we hypothesize:

- H1 a, b: The Task-Technology Fit will have a positive impact on the perceived usefulness of (a) EHEV and (b) EBEV with onboarded CEMG.
- H2 a, b: The Task-Technology Fit will have a positive impact on the perceived ease of use of the feature for (a) EHEV and (b) EBEV with onboarded CEMG.

- H3 a, b: The Task-Technology Fit will have a positive impact on the intention of adoption of (a) EHEV and (b) EBEV with onboarded CEMG.

3.2.2. Perceived Ease of Use

The perceived ease of use variable is the degree to which EV onboarded with CEMG is perceived to be simple to use and extract the intended information from [69]. TAM posits the criticality of measuring the impact of perceived ease of use on perceived usefulness and on the attitude towards the studied artifact [59,68]. Therefore, we hypothesize:

- H4 a, b: The perceived ease of use will have a positive impact on the perceived usefulness of the feature for (a) EHEV and (b) EBEV with onboarded CEMG.
- H5 a, b: The perceived ease of use will have a positive impact on the attitude towards (a) EHEV and (b) EBEV with onboarded CEMG.

3.2.3. Perceived Usefulness

The TAM's perceived usefulness variable indicates to which degree EV onboarded with CEMG will accomplish its intended function, which is to give perspective of the environmental benefits of using EV [69]. TAM assessed that perceived usefulness has a positive impact on both attitude toward the artifact in question and the intention of adopting said artifact [59,68]. Therefore, we hypothesize:

- H6 a, b: The perceived usefulness will have a positive impact on the attitude towards (a) EHEV and (b) EBEV with onboarded CEMG.
- H7 a, b: The perceived usefulness will have a positive impact on the intention of adoption of (a) EHEV and (b) EBEV with onboarded CEMG.

3.2.4. Attitude

Attitude being one of the correlated variables between TAM and TPB represents the consumer attitude regarding EV, which represents their position regarding symbolic and hedonic perspectives over EV [70]. TAM and TPB both assess the impact of attitude as positive towards the intention of adoption [47,59,68]. Therefore, we hypothesize:

- H8 a, b: The attitude towards EV will have a positive impact on the intention of adoption of (a) EHEV and (b) EBEV with onboarded CEMG.

3.2.5. Perceived Behavioral Control

The TPB's perceived behavior control variable refers to the consumer's belief that the behavior at hand is in his control [70]. In this study this translates to the belief that the consumer feels control over his own CO_2 emissions and that he is empowered to act on his pro-environmental position, mainly focusing on the symbolic perspective [47,68]. Therefore, we hypothesize:

- H9 a, b: The perceived behavioral control will have a positive impact on the intention of adoption of (a) EHEV and (b) EBEV with onboarded CEMG.

3.2.6. Subjective Norms

The TPB's subjective norm variable indicates the weight of social pressure to perform a determined function. This study translates this as the social influence perceived by the consumer [35,70] while sharing measured positive environmental impact and receiving feedback from peers [47,68]. Therefore, we hypothesize:

- H10 a, b: The subjective norm will have a positive impact on the intention of adoption of (a) EHEV and (b) EBEV with onboarded CEMG.

4. Data Collection and Research Methodology

Supported by the fact that acceptance studies have traditionally been conducted using survey research [71], the data collection for this research used an online questionnaire, made available through a well-known market tool, Qualtrics, and divulgated through email and social media groups. The questionnaire had an option to be answered in English or in Portuguese. In the design phase, the Portuguese questions were translated from the English ones and then reviewed by a different information systems academic to ensure the translation and ensure consistency. Our sample target comprised respondents who were more than eighteen years old, vehicle owners or people intending to buy one, or people with knowledge of electric vehicles. The questionnaire was built based on the research model, and constructs from earlier literature were employed, using a multiple-item 7-point Likert-type scale, ranging from “strongly disagree” (1) to “strongly agree” (7), assuming that this is one of the essential rating scales used as a measurement tool in literature [72]. In the beginning of the survey instrument, a section introducing EV and the CEMG integrated tool on the vehicles was presented. After this introduction, the questionnaire presented the measurement items separated by vehicle groups, Electric Hybrid Engine Vehicle and Electric Battery Engine Vehicle, with six sections each, representing the six different studied constructs, namely Task-Technology Fit [60,67], Perceived Ease of Use [59,68], Perceived Usefulness [59,68], Attitude [47,59,68], Perceived Behavioral Control, and Subjective Norms [47,68], as presented in Appendix A. To test the instrument and correct any errors, the questionnaire was pilot tested with a sample of 30 respondents that were not included in the final dataset. The initial results confirmed that the scales were reliable and valid, and therefore we proceeded to the next phase of data collection.

At the end of a period of 12 weeks collecting data, a total of 268 respondents were obtained. The submissions were IP-validated to ensure there were no multiple responses from the same user. From the initial amount, 131 respondents did not answer all the questions, and their responses were excluded. At the end the remaining 137 responses were used in our study contemplating two full datasets of answers, one for EHEV and another for EBEV. The respondent’s demographic characteristics are presented in Table 3.

Table 3. Respondents’ characteristics (from the authors).

	N	%
Gender		
Male	68	49.6
Female	69	50.4
Other/prefer not to say	0	0.00
Age		
18–24	5	3.65
25–34	29	21.16
35–44	17	12.41
45–54	47	34.31
55–64	34	24.82
Other/prefer not to say	5	3.65

Table 3. *Cont.*

	N	%
Education Level		
Secondary Level Graduate	7	5.11
College Graduate	92	67.15
Master	32	23.36
Doctorate	4	2.92
Other/prefer not to say	2	1.46
Employment Status		
Employed (full time)	96	70.07
Employed (part time)	9	6.57
Unemployed	3	2.19
Retired	15	10.95
Student	6	4.38
Other/prefer not to say	8	5.84

Common Method Bias (CMB) was validated using Random Dependent Variable [73,74] and Herman's single factor through SPSS version 30.0.0.0 (172) achieving a value of 48,902%, which is below the 50% threshold defined in previous literature [75].

5. Data Analysis and Results

The theoretical model was tested using partial least squares (PLSs), a structural equation modelling (SEM) approach [76]. SEM is an approach that combines multiple parts of the research process holistically. It is considered a second-generation analytical method that combines first-generation descriptive techniques with explanatory techniques [16]. Therefore, it combines a psychometric component by modelling latent variables such as subjective norms or intention towards EV adoption with an econometric perspective focused on estimating the cause-effect relationships between those same constructs. These models are known as measurement and structural models, respectively, and within this study they will be assessed separately [77]. The main advantage of the measurement model component is that the indicators used to measure each construct are subjected to measurement errors. Because each construct is measured through several items, the effects of measurement errors are reduced and controlled. In the structural model, SEM also enables researchers to model multiple independent and dependent variables simultaneously. There are two broad methods to conduct SEM. PLS is recognized to have fewer assumptions when compared to the covariance-based techniques. Hence, for these reasons, PLS was employed with SmartPLS 4.0, which is a convenient and powerful statistical technique considered appropriate for many research situations [76] and suitable for studying complex models with numerous constructs [78]. PLS is also considered adequate whenever the sample is more than 10 times greater than the maximum number of paths directed to a construct [79]. The theoretical model proposed was tested against two different datasets, namely from EHEV and EBEV groups, presented as follows.

5.1. Measurement Model

The measurement model was evaluated based on item reliability, which verified that the loading values were all above the 0.7 threshold [73]; internal consistency, which validated that the composite reliability and Cronbach's Alpha values were all above the 0.7 threshold [73]; and convergent validity, which was validated by checking that the average variance extracted (AVE) was above the 0.5 threshold value [80]. Composite Reliability, Cronbach's Alpha, and AVE values for EHEV and EBEV are presented in Tables 4 and 5, respectively.

Table 4. EHEV Internal Consistency (from the authors).

Construct	CR	CA	AVE
AT	0.879	0.879	0.892
IA	0.903	0.911	0.837
PBC	0.870	0.891	0.884
PEU	0.898	0.899	0.710
PU	0.831	0.833	0.855
SN	0.945	0.940	0.825
TTF	0.876	0.876	0.670

Legend: CR = Composite reliability, CA = Cronbach's Alpha, AVE = Average Variance Extracted, AT = Attitude, IA = Intention towards Electric Vehicle Adoption, PBC = Perceived Behavior Control, PEU = Perceived Ease-Of-Use, PU = Perceived Usefulness, SN = Subjective Norms, TTF = Task-Technology Fit.

Table 5. EBEV Internal Consistency (from the authors).

Construct	CR	CA	AVE
AT	1.000	1.000	1.000
IA	0.943	0.941	0.944
PBC	0.909	0.873	0.886
PEU	0.913	0.910	0.736
PU	0.934	0.929	0.876
SN	0.896	0.845	0.863
TTF	0.917	0.915	0.747

Legend: CR = Composite reliability, CA = Cronbach's Alpha, AVE = Average Variance Extracted, AT = Attitude, IA = Intention towards Electric Vehicle Adoption, PBC = Perceived Behavior Control, PEU = Perceived Ease-Of-Use, PU = Perceived Usefulness, SN = Subjective Norms, TTF = Task-Technology Fit.

When validating the model against the EHEV dataset, no items had to be discarded for the items reliability to be in an acceptable condition, as the loading values were all above the 0.7 threshold [73], as presented in Appendix B. When validating the model against the EBEV dataset, two items had to be discarded for the items' reliability to be in an acceptable condition, namely IA4-B and IA5-B, as their loading values were below 0.7 [73], as presented in Appendix C.

Discriminant validity validated that the loadings were all above the cross-loading values [81] and that the Fornell-Larcker criterion was fulfilled, guaranteeing that the square roots of AVE values should exceed the correlation between other constructs [80], as presented in Tables 6 and 7 for EHEV and EBEV, respectively. Data regarding loading and cross-loading are present on the tables of Appendices B and C for EHEV and EBEV, respectively.

Table 6. EHEV Fornell-Larcker Criterion (from the authors).

Construct	AT	IA	PBC	PEU	PU	SN	TTF
AT	0.944						
IA	0.801	0.914					
PBC	0.520	0.502	0.940				
PEU	0.702	0.647	0.639	0.842			
PU	0.761	0.702	0.595	0.771	0.924		
SN	0.428	0.464	0.437	0.327	0.408	0.908	
TTF	0.617	0.553	0.567	0.733	0.662	0.289	0.818

Legend: AT = Attitude, IA = Intention towards Electric Vehicle Adoption, PBC = Perceived Behavior Control, PEU = Perceived Ease-Of-Use, PU = Perceived Usefulness, SN = Subjective Norms, TTF = Task-Technology Fit.

Table 7. EBEV Fornell-Larcker Criterion (from the authors).

Construct	AT	IA	PBC	PEU	PU	SN	TTF
AT	1.000						
IA	0.786	0.972					
PBC	0.573	0.517	0.941				
PEU	0.593	0.555	0.573	0.858			
PU	0.816	0.758	0.570	0.675	0.936		
SN	0.445	0.472	0.464	0.327	0.402	0.929	
TTF	0.677	0.694	0.453	0.563	0.694	0.363	0.864

Legend: AT = Attitude, IA = Intention towards Electric Vehicle Adoption, PBC = Perceived Behavior Control, PEU = Perceived Ease-Of-Use, PU = Perceived Usefulness, SN = Subjective Norms, TTF = Task-Technology Fit.

Heterotrait-monotrait validation was also conducted, evaluating if the values encountered are below the recommended 0.9 threshold [82]. To meet this requirement, the items AT1-A and AT5-B had to be removed from the EHEV and EBEV datasets, respectively. HTMT values are presented in Tables 8 and 9 for EHEV and EBEV, respectively.

Table 8. EHEV Heterotrait-monotrait (from the authors).

Construct	AT	IA	PBC	PEU	PU	SN
IA	0.894					
PBC	0.589	0.563				
PEU	0.784	0.710	0.720			
PU	0.891	0.806	0.693	0.883		
SN	0.471	0.503	0.497	0.354	0.471	
TTF	0.701	0.616	0.644	0.824	0.770	0.316

Legend: AT = Attitude, IA = Intention towards Electric Vehicle Adoption, PBC = Perceived Behavior Control, PEU = Perceived Ease-Of-Use, PU = Perceived Usefulness, SN = Subjective Norms, TTF = Task-Technology Fit.

Table 9. EBEV Heterotrait-monotrait (from the authors).

Construct	AT	IA	PBC	PEU	PU	SN
IA	0.810					
PBC	0.604	0.564				
PEU	0.620	0.595	0.637			
PU	0.844	0.809	0.622	0.727		
SN	0.473	0.520	0.533	0.359	0.448	
TTF	0.706	0.746	0.499	0.613	0.752	0.412

Legend: AT = Attitude, IA = Intention towards Electric Vehicle Adoption, PBC = Perceived Behavior Control, PEU = Perceived Ease-Of-Use, PU = Perceived Usefulness, SN = Subjective Norms, TTF = Task-Technology Fit.

5.2. Structural Model and Hypothesis

During the collinearity validation step of the structural model on the EHEV dataset testing, five items had to be discarded so VIF values could reach values below the 5.0 threshold, namely AT3-A, AT4-A, IA2-A, IA3-A, and PU2-A [73,74]. For EBEV dataset testing, five items had to be discarded so VIF values could reach values below the 5.0 threshold, namely AT1-B, AT3-B, AT4-B, IA2-B, and SN3-B [73,74].

The assessment of the structural model and hypothesis testing are based on the examination of standardized paths. The path significance levels were estimated using bootstrapping through 5000 resampling method iterations [73]. The model analysis was also done separately for EHEV (or A) and EBEV (or B), as seen in Figures 3 and 4, respectively.

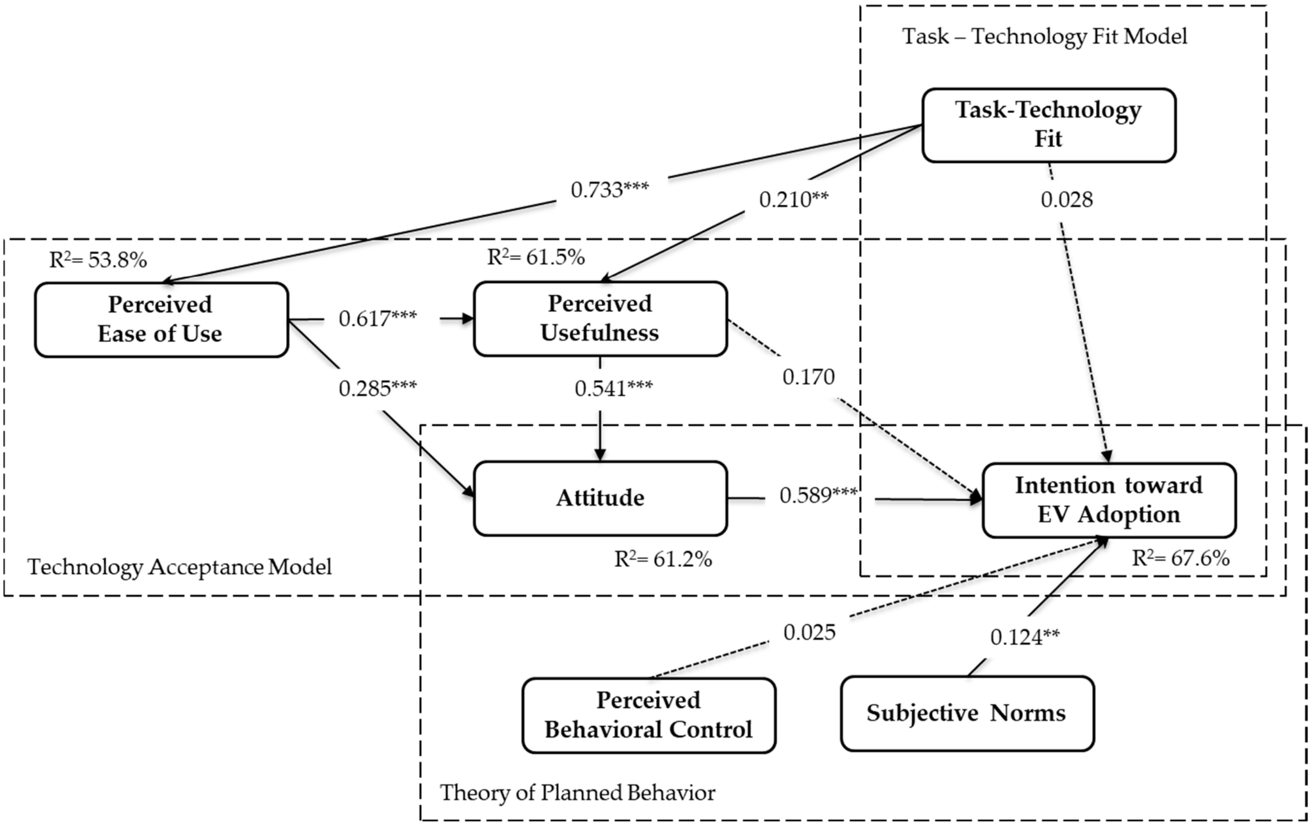

Figure 3. EHEV supported hypotheses and statistical significance (from the authors); Note: ** $p < 0.05$; *** $p < 0.01$, R^2 = coefficient of determination.

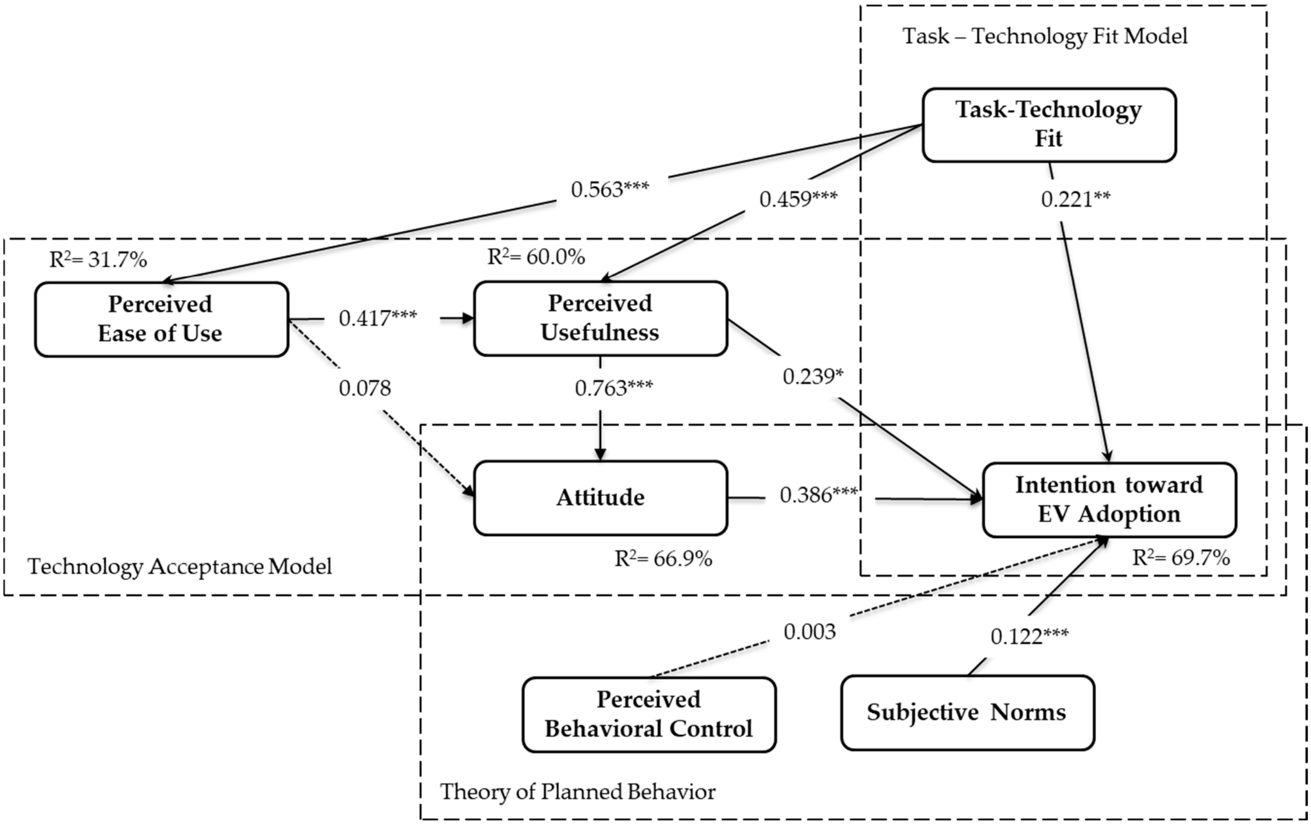

Figure 4. EBEV supported hypothesis and statistical significance (from the authors); Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$, R^2 = coefficient of determination.

Supported and rejected hypotheses are summarized in Table 10, presented as follows.

Table 10. Hypotheses results (from the authors).

EHEV (a)				EBEV (B)			
	Results	**Path Coefficient**	**Significance Level (*p*)**		**Results**	**Path Coefficient**	**Significance Level (*p*)**
H1a	Supported	0.210	0.026 **	H1b	Supported	0.459	0.000 ***
H2a	Supported	0.733	0.000	H2b	Supported	0.563	0.000 ***
H3a	Rejected	0.028	0.676	H3b	Supported	0.221	0.006 ***
H4a	Supported	0.617	0.000 ***	H4b	Supported	0.417	0.000 ***
H5a	Supported	0.285	0.000 ***	H5b	Rejected	0.078	0.225
H6a	Supported	0.541	0.000 ***	H6b	Supported	0.763	0.000 ***
H7a	Rejected	0.170	0.147	H7b	Supported	0.239	0.050 **
H8a	Supported	0.589	0.000 ***	H8b	Supported	0.386	0.000 ***
H9a	Rejected	0.025	0.770	H9b	Rejected	0.003	0.963
H10a	Supported	0.124	0.020 **	H10b	Supported	0.122	0.009 ***

Legend: ** $p < 0.05$; *** $p < 0.01$.

Overall, a total of seven hypotheses were found statistically significant in EHEV and eight in EBEV. The H3 and H7 hypotheses were supported in EBEV but not in EHEV, and in the H5 hypothesis the opposite happened; it was supported in EHEV but not in EBEV.

6. Discussion

Among the findings provided by this study, the coefficient of determination values related to the intention towards electric vehicle adoption, which explains 67.6% of the variation for the EHEV and 69.7% for the EBEV vehicles, are in line with previous literature values regarding technology intention to adopt with values such as 49.9% [83], 65.5% [69], and 84.0% [67]. Comparing the results of both vehicle groups, EHEV and EBEV, it is visible that some of the raised hypotheses can be supported or rejected based on what vehicle group is tested against the model. The hypotheses H3(a, b), which assesses the impact of TTF of EV onboarded with the CEMG feature on intention of adoption, was rejected when looking at EHEV vehicles (a) but supported when considering EBEV vehicles (b). Also, H5(a, b), which assesses the perceived ease-of-use of EV onboarded with the CEMG feature impact on attitude towards the vehicle group, was proven to be true when looking at EHEV vehicles (a), but not true when looking at EBEV ones (b). Interestingly, in both datasets, EBEV and EHEV, the hypothesis H9(a, b) was rejected, meaning that it can be stated that the perceived usefulness and the perceived behavior control of EV integrated with the CEMG feature are disassociated with the intention of adoption of EV.

For both EHEV and EBEV vehicle groups, supporting H1(a, b) and H2(a, b), TTF emerged as a critical factor in shaping consumers' perceived usefulness and perceived ease of use of EVs onboarded with the CEMG feature. This highlights that consumers' perception of how well technology aligns with their tasks influences their evaluation of its usefulness and ease of use. However, TTF impact on intention to adopt was found to be significant only for EBEV but not for EHEV. This discrepancy suggests that consumers may view the advanced technology in EBEV as a more critical factor in their adoption decisions compared to EHEV, where other factors such as fuel efficiency and cost may take precedence. The strong support for the TTF-PEU relationship in both groups suggests that consumers are particularly sensitive to the technology's usability, which aligns with previous research that emphasizes the importance of ease of use in technology adoption [16,67].

The perceived usefulness is strongly associated with attitude towards the vehicle for both EBEV and EHEV, supporting H6(a, b) and the notion that individual evaluations of vehicle utility significantly shape their attitudes, which is supported in previous literature involving perceived usefulness and attitude [67,68]. This finding aligns with TAM, where perceived usefulness is considered a key determinant of attitude and, subsequently, intention to adopt [59]. However, the relationship between perceived usefulness and intention to adopt was rejected when considering EHEV vehicle types, rejecting H7(a), but supported when considering EBEV vehicles, supporting H7(b). This finding is somewhat surprising in relation to hypothesis H7(a), as perceived usefulness is typically considered a strong predictor of adoption intention [13], although some earlier works also failed to establish this relationship [67,68]. One possible explanation could be that other external factors, such as cost, infrastructure, and government incentives, play a more influential role in the adoption of electric vehicles when fossil fuel aspects are still involved, as has been suggested in some earlier literature [13,47].

Perceived ease of use was shown to influence attitude towards the EV onboarded with the CEMG in EHEV vehicles H5(a), but its influence on attitude towards the EBEV group was rejected H5(b). This suggests that while PEU may impact attitude toward EHEV, it does not play a similar role for EBEV. This could indicate that EBEV consumers may be less concerned with the ease of use of the technology and more focused on other factors such as range, battery life, or the vehicle's overall performance. The influence of PEU on attitude for EHEV consumers suggests that simplicity and user-friendliness may be more highly valued in hybrid vehicles, which are often seen as transitional options for those hesitant to fully commit to electric driving.

Subjective Norm variable had a significant positive impact on Intention to Adopt for both EBEV and EHEV, supporting H10(a, b), and highlighting the social influence of others' opinions on consumers' decisions to adopt electric vehicles. This supports existing literature that suggests subjective norms play an essential role in technology adoption [70], particularly when it comes to new or innovative technologies [84].

Perceived behavioral control did not have a significant effect on Intention to Adopt in both vehicle groups, thus rejecting H9(a, b). This is consistent with some earlier studies that suggest PBC might be a weaker predictor of adoption in the context of electric vehicles, particularly in regions where external factors like government subsidies, environmental concerns, and infrastructure development may reduce perceived barriers to adoption [11,83]. Nevertheless, these results contradict some other earlier studies that supported the correlation between PBC and intention of adoption [68,70], even if they do not present information about external factors.

6.1. Theoretical and Practical Implications

This study contributes to the body of knowledge with an innovative model, as far as we know not yet tested in literature until now, by combining the Task-Technology Fit model, the Technology Acceptance Model, and the Theory of Planned Behavior. These models are usually used individually to assess technology adoption, but the three combined as a single and consolidated model to understand the acceptance of technology considering social and individual behavior factors in the context of electric vehicles is surely innovative. From a theoretical point of view, our model could be used in distinct subjects and technologies studies to better understand the adoption phenomenon, supporting future studies.

Given that TTF significantly impacts perceived ease of use and usefulness, manufacturers should actively promote the CEMG as a crucial tool for eco-conscious driving. By making emissions data visible, interpretable, and actionable, CEMG equipped vehicles can empower users to drive more efficiently, reducing their environmental impact. To strengthen its role, automakers could integrate AI-powered insights into CEMG, providing real-time feedback and customized recommendations on driving habits that minimize CO_2 emissions. The research underscores the importance of integrating CEMG into both vehicle design and consumer engagement strategies. By positioning it as an essential tool for sustainability, cost-efficiency, and regulatory alignment, manufacturers can boost consumer trust, enhance the perceived value of EHEV and EBEV models, and drive higher adoption rates. Additionally, leveraging CEMG for data-driven policymaking and corporate fleet optimization can further contribute to the decarbonization of the transportation sector by providing consumers with critical information regarding sustainable emission patterns that should positively impact EV adoption. Since consumer adoption is influenced by perceived benefits, manufacturers should focus on educating the public on how CEMG enables users to lower CO_2 emissions and contributes to fuel efficiency in hybrid models. Marketing campaigns could highlight real-world scenarios, comparative statistics, and user testimonials to showcase the effectiveness of CEMG. Additionally, brands could develop interactive digital tools or mobile apps that simulate the impact of different driving behaviors on emissions, allowing potential buyers to visualize and have more transparency on the benefits of using CEMG. If manufacturers enable CEMG-equipped vehicles to share anonymized emissions data with environmental agencies or smart mobility platforms, it could support broader CO_2 reduction initiatives. Governments could incentivize this practice by providing tax benefits or green certifications for vehicles that contribute to national emissions tracking programs. Additionally, business fleets and ride-sharing services could benefit from real-time CO_2 tracking, allowing them to optimize routes and fleet efficiency while demonstrating corporate sustainability efforts.

Smart cities, to be effective, need real-time or near real-time information. Continuous emissions monitoring gauges, like CEMG, applied to the smart cities' context, for instance, in illumination posts, traffic lights, ride-hailing services, shared fleets, or last-mile delivery vehicles in the urban environments, could provide the necessary data about greenhouse gases to the cities' management systems, better supporting decision-making, traffic flow management, and city levels of pollution management. In the long term, CEMG represents a promising solution to improve pollution emission data accuracy, timeliness, and adaptability in cities [85]. It could also help to create and control the compliance level with low-emission zones, for example, near hospitals, gardens, public buildings, commercial areas, monuments, or public areas with more people. These actions could potentially have a very important impact on citizens' quality of life and health, such as increasing the overall life expectancy and decreasing the risk of respiratory diseases [86]. Another important takeaway from our study is the power of information and perception. While tools like CEMG provide valuable insights about emissions, the extent to which consumers engage with and act upon this data depends on a complex interplay of psychological and external factors. The success of emission management technology hinges not only on its accuracy but also on its combination with smart-city systems and algorithms to better manage traffic and pollution, as well as on how effectively it is communicated, marketed, and integrated into the driver and citizen's experience.

6.2. Limitations and Future Research

While the study offers valuable insights, it is not without limitations. The generalization of the results is limited by the relatively small sample size obtained, and since almost 60% of the respondents are in the range of 45–64 years old, they may not fully represent the diversity of consumers across different regions. Future research could try to collect a larger sample size, increase the geographical range, and explore how different demographic parameters, such as income, region of residence, or city type, could affect vehicle adoption factors and decisions. We also acknowledge as a limitation the fact that housing type (single-family versus multi-family home) can influence EV adoption, since it is known that multi-family buildings often lack access to charging points that can become a barrier to adoption, as identified in some earlier studies [87,88]. Future endeavors could extend present work collecting and analyzing this variable. Longitudinal studies could also be valuable in tracking changes in consumer attitudes and adoption behaviors over time as the EV market matures [89]. Furthermore, future studies could explore different features or usages to further enrich the understanding of adoption drivers in the electric vehicle market, like the introduction of AI models for observability and even driving profile mapping. Studying the integration of CEMG with smart cities is another very interesting venue for future researchers to follow in more detail, collecting data and providing CO_2 emission information to citizens in locations such as traffic lights, streets, hospitals, or public buildings, reinforcing sustainability awareness. As CEMG features become more interconnected, understanding privacy and legal impacts on individual behavior and perceived data safety could also become an important avenue to follow. Culture is also known to influence adoption; studying how it could influence EV adoption and how they change among groups and countries could also be a very interesting area to study, completing some earlier studies on this subject [90].

This research findings also highlight persistent barriers related to infrastructure, cost, and consumer hesitation in fully transitioning to EV technology. Future research should continue to explore these limitations while also investigating regional variations, ethical concerns surrounding data use, and the potential for AI-driven eco-driving solutions. Additionally, integrating gamification and data-sharing initiatives could enhance the appeal and effectiveness of emission management tools, transforming them from passive monitors into active motivators for sustainable environmental driving habits. Another interesting topic that could not be assessed in this research is the impact of CEMG on flex-fuel vehicles based on hydrogen power cells, extending earlier studies on this matter [91,92]. Understanding the adoption of this new technology could generate valuable new insights into sustainability in the automotive sector. Understanding how EV onboarded with CEMG would respond as constructs of other models focused on assessing adoption of technology or individual behavior could further test the validity of using TTF, TAM, and TPB models together as an interesting multi-level acceptance model.

7. Conclusions

The transition toward sustainable transportation is no longer a distant vision; it is a real and urgent necessity. As climate change accelerates and urban air pollution increases, reducing carbon emissions in the transportation sector has become a fundamental pillar in the global sustainability efforts. Our study successfully explored the key factors influencing the intention of adoption of EBEV and EHEV. In more detail, task-technology fit, encompassing how the proposed CEMG observability feature is perceived by consumers, was found statistically significant for both EBEV and EHEV in the relationships with perceived ease of use and perceived usefulness, and with intention towards adoption in EHEV. Perceived ease-of-use influences perceived usefulness in both EBEV and EHEV, and the attitude only in EHEV. The relationship between Perceived usefulness and attitude was found to be statistically significant in both EBEV and EHEV, and with the intention towards adoption only in EHEV. The roles of subjective norms and attitudes towards electric vehicle adoption have been supported as imperative drivers of intention of adoption for both EHEV and EHEV groups. Task-technology fit and perceived usefulness only presented a positive impact on the intention of adoption in EBEV. Even with some differences in terms of the factors influencing different vehicle groups' adoption, according to the results presented, the findings underscore that technological advancements in fuel efficiency and CO_2 emission management, such as the CEMG, can play a crucial role in consumer decision-making and environmental awareness perception for both EHEV and EBEV. Ultimately, from a practical point of view, the widespread adoption of EBEV and EHEV is a promising solution with real environmental impact but requires a collaborative effort between governments, industry leaders, and consumers. By leveraging technological innovation, behavioral insights, and strategic policymaking, we can pave the way for more efficient and smarter cities, with transportation ecosystems genuinely sustainable for future generations.

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Informed Consent Statement: Informed consent was obtained from all individual participants included in this study.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed at the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Questionnaire Items

Construct	Item	Adaption	Source
Task-Technology Fit	TTF1	My EHEV/EBEV with an onboarded CEMG is enough for all my trips	[16]
	TTF2	I reach all my destinations on time with my EHEV/EBEV with an onboarded CEMG	
	TTF3	My EHEV/EBEV onboarded CEMG metrics range is enough for my daily needs	
	TTF4	An EHEV/EBEV onboarded CEMG is available when needed	[69]
	TTF5	An EHEV/EBEV onboarded CEMG can help me deal with unexpected situations	
Perceived Ease-of-Use	PEU1	I (will) find that driving an EHEV/EBEV with an onboarded CEMG is easy	[15]
	PEU2	My interactions with an EHEV/EBEV with an onboarded CEMG is easy for me to understand	[59]
	PEU3	An onboarded CEMG provides helpful guidance in performing tasks	
	PEU4	I will find it easy to understand my emission reduction using the onboarded CEMG	[67]
	PEU5	Being an onboarded feature, the CEMG makes it easier for me to use the EHEV/EBEV	[68]
Perceived Usefulness	PU1	The advantages of using an EHEV/EBEV with an onboarded CEMG (will) outweigh the disadvantages	[15]
	PU2	Overall, using an EHEV/EBEV with an onboarded CEMG is useful	[46]
	PU3	Using an EHEV/EBEV with an onboarded CEMG would make me safer	
Attitude	AT1	I would feel satisfied about myself if I bought an EHEV/EBEV with an onboarded CEMG	[46]
	AT2	I take pride in owning an EHEV/EBEV with an onboarded CEMG	
	AT3	I like the idea to own an EHEV/EBEV with an onboarded CEMG	
	AT4	All things considered, using an EHEV/EBEV with an onboarded CEMG is a good idea	[69]
	AT5	All things considered, using an EHEV/EBEV with an onboarded CEMG is advisable	
Subjective Norms	SN1	Most people that are important to me own an EHEV/EBEV with an onboarded CEMG	[35]
	SN2	I believe that many people who are important to me expect me to own/choose an EHEV/EBEV with an onboarded CEMG	
	SN3	People who are important to me have suggested that I switch to an EHEV/EBEV with an onboarded CEMG	

Construct	Item	Adaption	Source
Perceived Behavioral Control	PBC1	I am in full control of using an EHEV/EBEV with an onboarded CEMG to understand my emission reduction	[83]
	PBC2	I have enough knowledge to use an EHEV/EBEV with an onboarded CEMG to understand my emission reduction	
Intention toward EV Adoption	IA1	I expect to drive an EHEV/EBEV with an onboarded CEMG in the near future	[46]
	IA2	I have the intention to drive an EHEV/EBEV with an onboarded CEMG in the near future	
	IA3	Assuming I had the opportunity, I would intend to buy an EHEV/EBEV with an onboarded CEMG	[10]
	IA4	Given that I had the opportunity, I predict that I would buy an EHEV/EBEV with an onboarded CEMG	

Appendix B. EHEV Loadings and Cross-Loadings (From the Authors)

	AT	IA	PBC	PEU	PU	SN	TTF
AT1-A	0.918	0.759	0.489	0.735	0.791	0.351	0.658
AT2-A	0.900	0.777	0.499	0.661	0.675	0.415	0.581
AT3-A	0.952	0.797	0.463	0.652	0.722	0.344	0.606
AT4-A	0.968	0.798	0.478	0.677	0.766	0.354	0.641
AT5-A	0.934	0.750	0.485	0.664	0.764	0.396	0.583
IA1-A	0.753	0.929	0.444	0.654	0.649	0.394	0.536
IA2-A	0.753	0.955	0.417	0.618	0.650	0.391	0.521
IA3-A	0.821	0.950	0.412	0.625	0.707	0.355	0.544
IA4-A	0.834	0.944	0.454	0.612	0.709	0.410	0.562
IA5-A	0.659	0.834	0.484	0.501	0.543	0.479	0.409
PBC1-A	0.544	0.491	0.953	0.654	0.621	0.380	0.560
PBC2-A	0.415	0.397	0.927	0.540	0.499	0.448	0.500
PEU1-A	0.576	0.497	0.572	0.859	0.667	0.144	0.661
PEU2-A	0.543	0.491	0.617	0.855	0.607	0.245	0.620
PEU3-A	0.551	0.482	0.559	0.872	0.628	0.350	0.601
PEU4-A	0.685	0.636	0.463	0.800	0.660	0.332	0.596
PEU5-A	0.682	0.628	0.495	0.827	0.760	0.305	0.605
PU1-A	0.739	0.656	0.598	0.793	0.941	0.304	0.689
PU2-A	0.754	0.655	0.564	0.770	0.951	0.278	0.695
PU3-A	0.714	0.654	0.502	0.626	0.877	0.456	0.529
SN1-A	0.247	0.270	0.385	0.227	0.273	0.845	0.180
SN2-A	0.390	0.459	0.460	0.346	0.364	0.945	0.300
SN3-A	0.411	0.418	0.342	0.296	0.355	0.931	0.282

	AT	IA	PBC	PEU	PU	SN	TTF
TTF1-A	0.508	0.409	0.412	0.597	0.527	0.197	0.862
TTF2-A	0.536	0.509	0.428	0.582	0.571	0.210	0.849
TTF3-A	0.578	0.449	0.418	0.594	0.595	0.153	0.830
TTF4-A	0.503	0.481	0.544	0.592	0.527	0.400	0.789
TTF5-A	0.557	0.436	0.511	0.628	0.608	0.225	0.759

Appendix C. EBEV Loadings and Cross-Loadings (From the Authors)

	AT	IA	PBC	PEU	PU	SN	TTF
AT1-B	0.962	0.799	0.529	0.610	0.795	0.419	0.700
AT2-B	0.942	0.801	0.573	0.594	0.815	0.463	0.677
AT3-B	0.975	0.832	0.519	0.582	0.803	0.409	0.710
AT4-B	0.96	0.819	0.512	0.585	0.819	0.417	0.705
AT5-B	0.948	0.821	0.536	0.580	0.815	0.478	0.688
IA1-B	0.776	0.955	0.517	0.518	0.721	0.505	0.633
IA2-B	0.854	0.979	0.508	0.531	0.737	0.453	0.704
IA3-B	0.844	0.976	0.489	0.560	0.751	0.436	0.713
PBC1-B	0.589	0.537	0.954	0.588	0.600	0.441	0.467
PBC2-B	0.447	0.431	0.928	0.478	0.458	0.452	0.376
PEU1-B	0.478	0.429	0.445	0.813	0.529	0.123	0.456
PEU2-B	0.481	0.405	0.542	0.866	0.534	0.245	0.442
PEU3-B	0.492	0.445	0.529	0.867	0.577	0.418	0.460
PEU4-B	0.586	0.547	0.520	0.866	0.604	0.335	0.508
PEU5-B	0.589	0.527	0.425	0.876	0.639	0.259	0.539
PU1-B	0.820	0.749	0.594	0.690	0.947	0.395	0.657
PU2-B	0.811	0.712	0.500	0.660	0.948	0.313	0.660
PU3-B	0.740	0.667	0.501	0.538	0.913	0.450	0.631
SN1-B	0.335	0.366	0.364	0.230	0.317	0.864	0.341
SN2-B	0.473	0.485	0.485	0.360	0.417	0.960	0.337
SN3-B	0.448	0.468	0.456	0.300	0.399	0.959	0.286
TTF1-B	0.614	0.602	0.328	0.410	0.605	0.270	0.861
TTF2-B	0.647	0.668	0.340	0.453	0.632	0.268	0.906
TTF3-B	0.603	0.553	0.452	0.563	0.559	0.144	0.845
TTF4-B	0.658	0.619	0.474	0.551	0.627	0.439	0.870
TTF5-B	0.618	0.602	0.356	0.453	0.571	0.351	0.837

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