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Understanding the Determinants of Sustainability and Adoption on the Automotive Sector

Private sector influence on drivers of adoption and consumption of electric vehicles

Vitor Figueiredo

Dissertation

presented as partial requirement in the obtention of the master's in information management degree.

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

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UNDERSTANDING THE DETERMINANTS OF SUSTAINABILITY AND ADOPTION ON THE AUTOMOTIVE SECTOR

by

Vitor Figueiredo

Master Thesis presented as partial requirement for obtaining the Master's degree in Information Management, with a specialization in Information Systems and Technologies Management.

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism, any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisboa, 26/02/2025

Vitor Figueiredo

ABSTRACT

The transportation sector is one of the largest contributors to the 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, behavioural, and economical factors. This research uses as artifact the CO2 Emission Management Gauge, or CEMG, to understand how the private sector, with onboarded features on vehicles, could potentialize sales and drive the movement towards electric vehicle adoption. This study implements an innovative new theoretical model based on Task-Technology Fit, Technology Acceptance, and on the Theory of Planned Behaviour to understand the main drivers that foster electric hybrid and electric battery engine vehicles adoption while providing private sector actors with insightful implications for using observability as a sustainable driver to foster electric vehicle adoption. The theoretical model was tested in a quantitative study with structural equation modelling (SEM), conducted in a South European country. Our findings reveal that while technological innovations like the CEMG provide consumers with valuable transparency regarding emissions, its influence on the intention of adoption is highly dependent on the attitude towards electric vehicle and subjective norm. Our results also support the influence of task-technology fit on perceived usefulness and perceived ease-of-use, influence of perceived usefulness on consumer attitude towards electric vehicles, and influence of perceived ease-of-use on perceived usefulness for both electric hybrid engine vehicles and electric battery engine vehicles. The different vehicle groups presented different impact levels on intention adoption based on perceived usefulness and task-technology fit as direct drivers of adoption. While our findings shows that the consumer’s perceived ease-of-use on electric hybrid engine vehicles onboarded with CEMG positively impacts their attitude towards it, the same impact was not proven when considering electric battery engine vehicles. Also, when considering electric battery engine vehicles onboarded with CEMG, the perceived usefulness and task-technology fit presented positive impact on the intention of adoption, the same was not true when looking at electric hybrid engine vehicles.

KEYWORDS

Sustainability; Electric Vehicle; Adoption; Observability; Private Sector.

Sustainable Development Objectives (SDO):

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LIST OF ACRONYMS AND ABBREVIATIONS

AFV	Alternative Fuel Vehicle
AVE	Average Variance Extracted
BEV	Battery Electric Vehicle
CEMG	CO2 Emission Management Gauge
CO2	Electric Vehicles
EBEV	Electric Battery Engine Vehicle
EGT	Evolutionary Game Theory
EHEV	Electric Hybrid Engine Vehicle
EV	Electric Vehicle
FCV	Fossil Combustion Vehicle
FFV	FlexFuel Vehicle
GWP	Global Warming Potential
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
LCA	Life Cycle Assessment
NEEV	Non-Electric Engine Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
PLS	Partial Least Squares
SEM	Structural Equation Modelling
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviour
TTF	Task-Technology Fit
VBN	Value Belief Norm

1. INTRODUCTION

Carbon dioxide (CO2) is the main greenhouse gas of which one-fifth is emitted by road transport (European Commission, 2012), making transport-emitted CO2 the major responsible of air pollution (Egbue & Long, 2012; Hoen et al., 2014). Reducing it is considered to be a key to preserve the environment (Anowar et al., 2017). Electric Vehicles (EVs) have increasingly been promoted on the market as a solution to reduce environmental problems (Thiel et al., 2010). One of the policies being implemented by many governments is the incentive on production and consumption of alternative fuel vehicles (AFVs). Instead of relying solely on fossil sources of fuel, AFVs can use alternative ones such as electricity, for EVs, and bioethanol and biogas for flexfuel vehicles (FFV), both offering promises on future transport development (Borén et al., 2017). Recently, AFVs have shown great share increase on the automotive market share numbers (Sierzchula et al., 2012), when considering the US market, AFVs had an increase of 9% from 1,53 million in 2022 to 1,7 million in 2023 (Singer et al., 2025). With the increasing incentives fomenting EVs in the different markets, it is crucial for companies to understand how to leverage sales and drive adoption, now more than ever. In 2023, the worldwide market stock of electric vehicle in the streets was 41 million, with an impressive increase of 51.8% from the previous year when the number was 27 million vehicles (International Energy Agency, 2024), while projections point that this number could scale up to 439.2 million by 2035, expressing 42.5% of the worldwide vehicles account (Rietmann et al., 2020)

Although research is extensive on individual and public levels (Degirmenci & Breitner, 2017; Encarnação et al., 2018; Gärling & Thøgersen, 2001; Schuitema et al., 2013), one of the gaps from past literature is the absence of information on how the private sector can generate impact in the intention of adoption of EVs. From previous literature, it becomes visible that it is imperative to better understand and deepen the analysis on how different determinants of EV customer' acceptance, triggers of first usage (Roemer & Henseler, 2022), satisfaction perception and continuance intention factors (Cruz-Jesus et al., 2023) interact and how they are measured and perceived. That said, even if some research on public actors' impact on consumer adoption of EVs have been made earlier the gap to the private counterpart is noticeable, therefore one of this study's objective is to provide empirical evidence on the determinants of environmental strategy in the automotive market by the private sector by developing an innovative theoretical model, as far as we know, not yet tested in literature.

One of the keys to understand if sustainability is being achieved is measuring and understanding emissions. Our research will focus on the impact of a CO2 Emission Management Gauge (CEMG), which can be an onboarded tool based on Life-Cycle Assessment (LCA) measuring how much emissions the consumer is emitting when using determined vehicle based on use phase average calculations, could provide the consumer with real time emission reduction information (Hawkins et al., 2012; Lubecki et al., 2025; Maselli et al., 2025; Picatoste et al., 2022). In more detail, the main research objectives are the following:

1) Identify and describe the most important sustainability and individual behaviour models and variables from previous literature.
2) Design an innovative theoretical model based in sustainability, technology, and individual behaviour factors.
3) Examine the effects of sustainability features p on individual behaviour.

4) Identify best practices to follow in the automotive sector.

This research starts by describing the current environmental scenario, presenting an overview of determinants of adoption of the EV technology by the social and public sectors as well as explaining the innovativeness of this research and its focus as an introductory chapter. The research will continue with a literature review focused on exploring previously studied determinants and classifying them to better understand how they interact with each other and with private sector measures and how they impact individual behaviour on a consumer level The literature review will also analyse interesting models previously used to understand adoption impact. The analysis of these determinants will be made through a new and innovative theoretical model designed combining models from previous literature and adapted to the new drivers and constraints presented by the research focus after a model evaluation section. The analysis should enable the research to present a result discussion, theoretical and practical implications, and the research conclusions.

2. LITERATURE REVIEW

2.1. ELECTRIC VEHICLES (EV)

The year that predictions assume for the complete depletion of oil resources in the world is 2038 (Ehsani et al., 2018) and EVs have been largely studied as viable alternatives in order to reduce the effects of an oil-centred and heavy-polluting transport market (Clement et al., 2009; Hajimiragha et al., 2010). This transition for pro-environmentally focused options is often seen with scepticism by automotive sector that, until recently, didn't provide its consumers with knowledge or experience about EV as alternatives (Gärling & Thøgersen, 2001; Lubecki et al., 2025; Picatoste et al., 2022; Sierzchula et al., 2012).

EVs are not new, they have been around for decades, the use of rechargeable batteries as vehicles power source date from the 19th century (Daziano & Chiew, 2012; Koprubasi, 2008; Schuitema et al., 2013). Nevertheless, due to non-competitive prices, some mass-production difficulties, and mainly a very strong and aggressive fuel market didn't allow them to become mainstream, and the internal combustion engine (ICE) oriented vehicles have been indisputable dominating the market (Schuitema et al., 2013), until now. Recent advances on 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 (Roemer & Henseler, 2022).. 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 in order to assign a better fit for consumer needs (Rezvani et al., 2015).

For the purpose of this study, vehicles will be separated in three groups, the first will be called non-electric engine vehicles (NEEV) 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 (EHEV) grouping vehicles that present an ICE but also an electric drivetrain representing hybrid electric vehicles (HEVs) and plug-in hybrid electric vehicles (PHEVs). PHEVs provides the possibility of recharging the electric drivetrain through the electric grid. The last group will be named electric battery engine vehicles (EBEV) 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 in order to be used which encompass and define battery electric vehicles (BEVs) (Chan, 1993; Ding et al., 2017; Hawkins et al., 2012; Jansson et al., 2017).

Table 1 - Vehicle Group Composition (Chan, 1993; Ding et al., 2017; Hawkins et al., 2012; Jansson et al., 2017)

Vehicle Group	Composition
NEEV	FFVs; FCVs;
EHEV	HEVs; PHEVs;
EBEV	BEVs;

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

Research on what drives EV adoption is extensive and the determinants that have been studied and successfully associated with adoption are numerous but the focus on the public sector, that encompasses governments and governmental actions, and social sector, which represents the consumer and its consumption habits, is noticeable. This leaves a certain gap on how the private sector, encompassing the companies and brands, can assess their weight on this equation. It is important to take into consideration that when talking about EVs adoption, the intent of adoption of technological innovativeness is what is being measured (Huijts et al., 2012) as the intention to adopt and actual adoption share the determinants and differ only in prediction assertiveness (Schuitema et al., 2013).

2.2.1. Governmental Support and Social Proactivity

Drivers of adoption are not always associated and dependant solely on consumers. Previous literature analyses and states the importance of public sector support and pro-environmental position, 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 (Encarnação et al., 2018; Shang et al., 2024). Opinion leading also rises as a critical point that can be associated with governmental actions, such as regulatory pressure in Germany (Roemer & Henseler, 2022) or fiscal incentives in the UK (Graham-Rowe et al., 2012), and are major drivers of adoption (Jansson et al., 2017) as influential leaders can shape social perception (Venkatraman, 1989; Weimann et al., 2007) and facilitate the diffusion of innovation process on this scenario (Rogers, 2003). Previous research also delves into how strengthening the engagement between inter-state institutions that dominate official deliberations would enhance sustainability governance, mainly by regulatory cooperation (Abbott et al., 2015), 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 Programme (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 (Abbott, 2012; Pattberg, 2010).

Public sector incentives have been proven critical for EVs acquisition (Sierzchula et al., 2012), but other variables also weight in and other needs have to be met. 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 (Encarnação et al., 2018).

The adoption of EVs intersects significantly with the proactive involvement of the social sector as pointed out in previous literature in order to increase demand after public-social dialog have taken place (Encarnação et al., 2018). This involvement may have a multitude of different triggers and previous research analyses key points of it by separating these factors into symbolic, instrumental and hedonic attributes (Schuitema et al., 2013).

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 creates a positive effect on adoption (Schuitema et al., 2013). This perception in regards to EV can be explained by the Self-image Congruency Theory (Sirgy, 1982), 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 on the adoption of electric vehicles as it can shape the consumer's self-image (Jansson et al., 2017; Roemer & Henseler, 2022) and still be influenced by other sectors with environmental marketing campaigns and other types of public advertising focusing on bridging consumers intentions and actions (Encarnação et al., 2018).

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 (Barbarossa et al., 2015; Roemer & Henseler, 2022). 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 (Axsen & Kurani, 2009; Jansson et al., 2017). This positive impact is supported by diffusion of innovation (Rogers, 2003) 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.

2.2.3. Instrumental Attributes

Functionalities and utilities which are presented by a product or technology impact directly and indirectly the way the potential adoption will take place (Dittmar, 1992). In the case of EVs, empirical evidence from previous literature studies shows the relevance of a few instrumental topics to the adoption and consumption of EVs such as pricing, usage costs, maintenance, performance, range, and infrastructure (Graham-Rowe et al., 2012; Skippon & Garwood, 2011). These instrumental topics can be grouped into another classification consisting of ease of use, relative advantage and perceived risks separated do better understand drivers of adoption (Roemer & Henseler, 2022). 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 is a strong driver in the direction of adoption and usage (Schuitema et al., 2013; Vandecasteele & Geuens, 2010). 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 a product usage (Dittmar, 1992; Roemer & Henseler, 2022).

Table 2 - Determinant Organization (Encarnação et al., 2018; Jansson et al., 2017; Roemer & Henseler, 2022; Schuitema et al., 2013)

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

2.3. SUSTAINABILITY AS A DRIVER

Governmental incentives on the production and consumption of EVs is a key factor on EV adoption by the social sector and, consequently, on the reduction of CO2 emissions. Taking this into consideration, it is of crucial importance to carefully calculate sustainability values as metrics often consider only tail pipe emissions, which are only one of the considerable aspects raised on EVs adoption impacts (Lave et al., 1995). The tool that has been constantly implemented by studies when it comes to CO2 emission measures by transport options has been the Life Cycle Assessment (LCA). LCA revolves around computing the production, usage, supply chain and disposal. It quantifies emissions and resources usage along the product life cycle measuring them on Global Warming Potential (GWP) calculated on grams of emission of CO2 per kilometre of usage (eCO2g/km) (Hawkins et al., 2012). LCA has been previously used on numerous studies and its model have been incremented continuously since its conception (Baptista et al., 2009; Daniel & Rosen, 2002). 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 (Wang et al., 1997) and 2-series (Burnham et al., 2006). The LCA model can become as complex as the extent of the due diligence of processes and suppliers can be assessed so in order to reduce system complexity (Jannesar Niri et al., 2024), a few purpose negligible items may be excluded from calculations providing us with the simplified life-cycle structure (Hawkins et al., 2012) for the different vehicle groups considered in this study presented in figure 1.

One key aspect that is critical to consider when understanding how NEEV, EHEV, and EBEV vehicles fit into LCA is the most relevant components of the three mentioned life cycles are rather similar and what will provide the significant difference on the overall analysis are the values of resource consumption and emission releases on the individual processes and components (Dewulf et al., 2010; Hawkins et al., 2012).

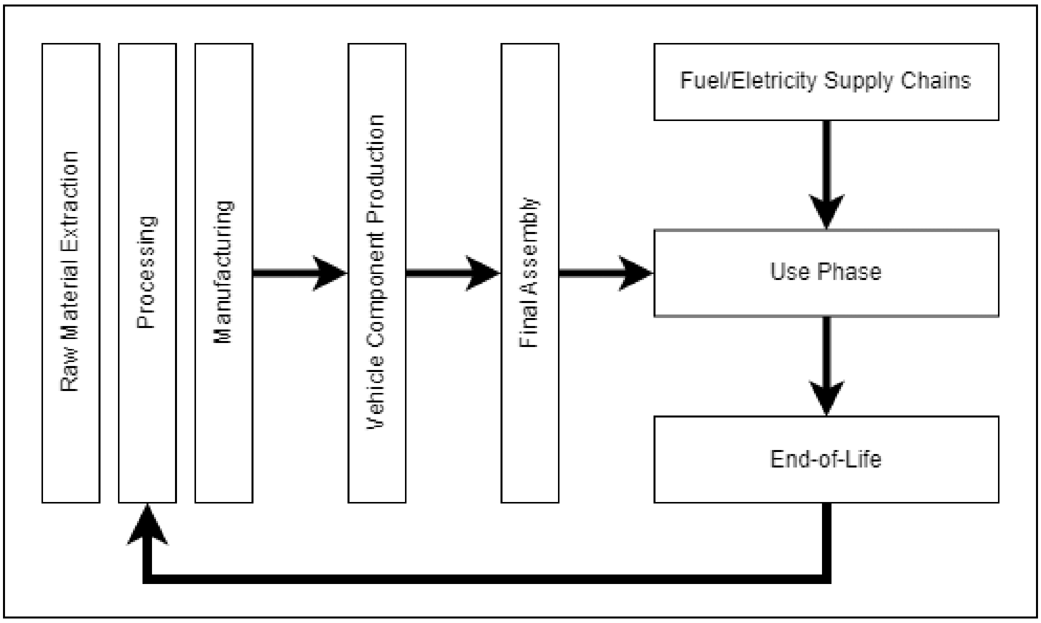

Figure 1 - Simplified NEEV, EHEV, and EBEV vehicles life cycle (Hawkins et al., 2012)

Previous literature successfully implemented LCA in order to better understand the different emission levels on different type of vehicles, including NEEV, EHEV and EBEVs. The results pointed out that when taking in 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 is numerically similar to the emissions of battery production on EBEV vehicles (Hawkins et al., 2012). An important topic when understanding the use phase, which consists on analysing driving and charging patterns, maintenance, and part replacement , on EBEV vehicles and EHEV vehicles, specifically the PHEVs, is that there is a large difference on 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 the coal, natural gases and non-fossil resources.

2.4. Determinants Interaction

Numerous theoretical models, such as the theory of planned behaviour (TPB) (Ajzen, 1985), the value belief norm theory (VBN) (Stern, 2000), technology acceptance model (TAM) (Davis, 1989), and other models (Goodhue & Thompson, 1995; Rogers, 2003), have been previously used to try to understand and predict the impact of EVs adoption on the automotive market (Glerum et al., 2014; Jensen et al., 2017; Plötz et al., 2014), 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 future regarding the technology (Egbue & Long, 2012; Giffi et al., 2011).

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 EVs adoption (Encarnação et al., 2018) by utilizing Evolutionary Game Theory (EGT) (Smith, 1988) proves that the public environmental position and the public support, which is enhanced by the first, causes 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) (Stern, 2000) which managed to perceive that social green self-identity causes direct impact on social environmental position and social influence and that the social environmental position is also responsible of mediating these social influence aspects (Barbarossa et al., 2015). The three considered attribute aspects (instrumental, symbolic and hedonic) also had their interaction previously mapped using Theory of Planned Behaviour (TPB) (Ajzen, 1985) where the instrumental attributes were proven to be mediated by symbolic and hedonic ones on the intention of adoption of EVs (Schuitema et al., 2013). Comprehension of how the instrumental attributes impact adoption have also been analysed and previous research using Technology Acceptance Model (TAM) (Davis, 1989) 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 (Roemer & Henseler, 2022). Regarding the private measures intended to enhance the intention of adoption and actual adoption, the Task-Technology Fit Model (TTF) (Goodhue & Thompson, 1995) has been largely used to assess the effectiveness of information systems (IS) solutions based on the provided tasks, functionalities and individual performance such as creating a comprehensive assessment of the success of the implementation of mobile ISs (Gebauer et al., 2010).

3. RESEARCH MODEL

The theoretical model developed in this research embraces observability features provided by the private sector and how they drive adoption and test 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 of 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. An 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

Several earlier studies managed to aggregate different models to further understand intention and consumer adoption (Dishaw & Strong, 1999; Irawan et al., 2022). Our theoretical model integrates the TAM (Davis, 1989), which provides the main body of structure to understand adoption, with TPB's (Ajzen, 1985) social influencing variables Perceived Behavioural Control and Subjective Norm, and TTF (Goodhue & Thompson, 1995), enabling us to further understand how the monitoring features provided by the private sector can impact. By using a combination of these three well stablished 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 onboarding emission observability features are available.

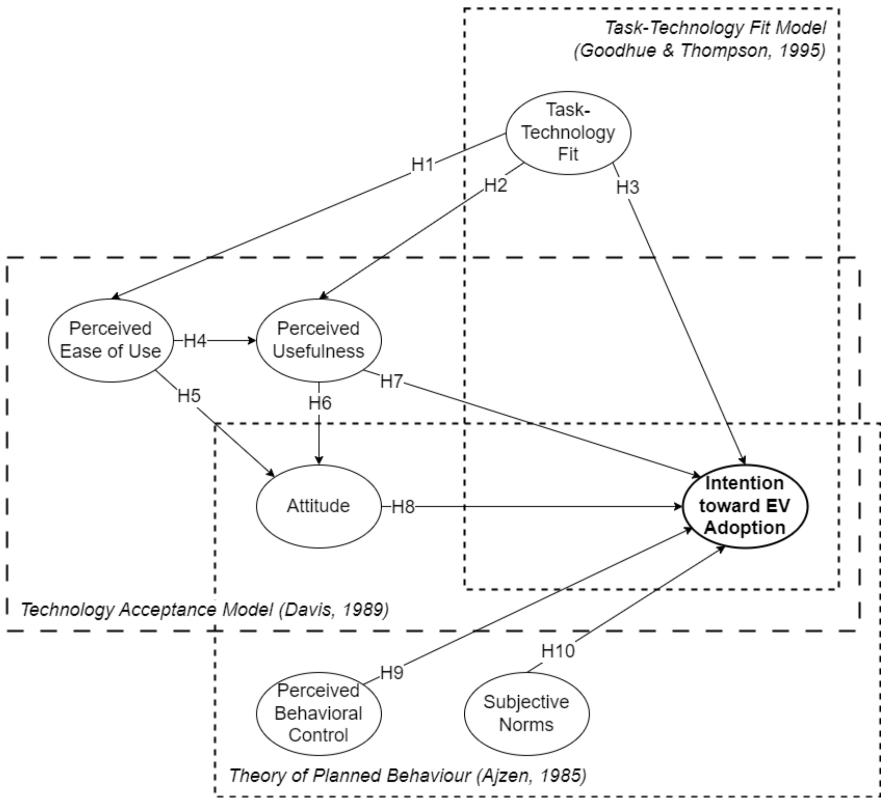

Figure 2 - Conceptual model involving TTF, TAM and TPB

3.2. HYPOTHESES

3.2.1. Task-Technology Fit

Task-technology fit provides the rational 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 (Cruz-Jesus et al., 2023). The relation of TTF and Perceived Ease of Use works mainly on providing further understanding on the technology capabilities while the relation of TTF with Perceived Usefulness and Intention of adoption are the actual key components of these model aggregations (Dishaw & Strong, 1999; Goodhue & Thompson, 1995). Therefore, we hypothesize:

- H1 a-b: The Task-Technology Fit will have a positive impact on the perceived usefulness on (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 TAM's perceived ease of use variable is the degree to which EVs onboarded with CEMG is perceived to be simple to use and extract the intended information from (Kim et al., 2010). TAM posits the criticality of measuring the impact of perceived ease of use on perceived usefulness and on the attitude towards the studied artifact (Davis, 1989; Irawan et al., 2022). 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 EVs onboarded with CEMG will accomplish its intended function, which is to give perspective of the environmental benefits of using EVs (Kim et al., 2010). TAM assessed that perceived usefulness has positive impact in both attitude toward the artifact in question and that intention of adoption said artifact (Davis, 1989; Irawan et al., 2022). 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 EVs, which represents their position regarding symbolic and hedonic perspectives over EVs (Pamidimukkala et al., 2025). TAM and TPB both assess the impact of attitude as positive towards the intention of adoption (Axsen & Kurani, 2009; Davis, 1989; Irawan et al., 2022). Therefore, we hypothesize:

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

3.2.5. Perceived Behavioural Control

The TPB's perceived behaviour control variable refers to the consumer's belief that that the behaviour at hand is in his control (Pamidimukkala et al., 2025). In this study this translates to the belief that the consumer feels control over his own CO2 emissions and that it is empowered to act on his pro-environmental position mainly focusing on the symbolic perspective (Axsen & Kurani, 2009; Irawan et al., 2022). Therefore, we hypothesize:

- H9 a-b: The perceived behavioural 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 (Jansson et al., 2017; Pamidimukkala et al., 2025) while sharing measured positive environmental impact and receiving feedback from peers (Axsen & Kurani, 2009; Irawan et al., 2022). 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

Data collection for this research was done by creating an online questionnaire, made available through a market well-known tool, Qualtrics, and divulgated through email and social media groups. The questionnaire had an option to be answered in English or in Portuguese language where the Portuguese questions were translated from the English ones. Our sample target compromised more than 18 years old respondents, vehicle owners or intending to buy one, people with knowledge on electric vehicles. The questionnaire was built based on the research model and constructs from previous literature were employed, using a multiple-item 7-point Likert-type scale, ranging from “strongly disagree” (1) to “strongly agree” (7). To begin, a section introducing EVs and the CEMG onboarded 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 (Dishaw & Strong, 1999; Goodhue & Thompson, 1995), Perceived Ease of Use (Davis, 1989; Irawan et al., 2022), Perceived Usefulness (Davis, 1989; Irawan et al., 2022), Attitude (Axsen & Kurani, 2009; Davis, 1989; Irawan et al., 2022), Perceived Behavioural Control (Axsen & Kurani, 2009; Irawan et al., 2022) and Subjective Norms (Axsen & Kurani, 2009; Irawan et al., 2022), as presented in Appendix A.

Our study had a total of 268 respondents in a period of 12 weeks. The submissions were IP-validated to ensure there were no multiple responses from the same user. From the initial amount, 131 respondents didn’t finish answering all the items and their responses were excluded. At the end the remaining 137 responses were used in our study. Data regarding the demographic of respondents is present on Appendix B.

Common Method Bias (CMB) was validated using Random Dependant Variable (Hair et al., 2021; Kock et al., 2012) and Herman’s single factor through SPSS achieving a value of 48,902% which is below the 50% threshold defined in previous literature (Podsakoff et al., 2003).

5. DATA ANALYSIS AND RESULTS

The theoretical model was tested using partial least squares (PLS), a structural equation modelling (SEM) approach (Ringle et al., 2022). 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 (Cruz-Jesus et al., 2023). 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 the measurement and structural models, respectively, and in this study they will be assessed separately (Anderson & Gerbing, 1988). 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 (Ringle et al., 2022), suitable for studying complex models with numerous constructs (Chin, 1998). PLS is also considered adequate whenever the sample is more than 10 times greater than the maximum number of paths directed to a construct (Gefen & Straub, 2005).

One crucial point to be stated regarding the data analysis is that the theoretical model proposed will be tested against two different datasets. The questionnaire items were built considering answers regarding vehicles from the EHEV and EBEV groups, presented as follow.

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 (Hair et al., 2021), internal consistency that validated that the composite reliability and Cronbach's Alpha values were all above the 0.7 threshold (Hair et al., 2021), convergent validity, which was validated by checking that the average variance extracted (AVE) was above the 0.5 threshold value (Fornell & Larcker, 1981). Composite Reliability, Cronbach's Alpha and AVE values for EHEV and EBEV are presented in tables 3 and 4, respectively.

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 (Hair et al., 2021) as presented in the table in appendix C.

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 (Hair et al., 2021) as presented in the table in appendix D.

Table 3 - EHEV Internal Consistency

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 Behaviour Control, PEU = Perceived Ease-Of-Use, PU = Perceived Usefulness, SN = Subjective Norms, TTF = Task-Technology Fit

Table 4 - EBEV Internal Consistency

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 Behaviour Control, PEU = Perceived Ease-Of-Use, PU = Perceived Usefulness, SN = Subjective Norms, TTF = Task-Technology Fit

Discriminant validity validated that the loadings were all above the cross-loading values (Götz et al., 2010) and that the Fornell-Larcker criterion was fulfilled guaranteeing that the square roots of AVE values should exceed the correlation between other constructs (Fornell & Larcker, 1981) as presented in tables 5 and 6 for EHEV and EBEV, respectively. Data regarding loading and cross loading is present on the tables of appendixes C and D for EHEV and EBEV respectively. Heterotrait-monotrait validation was also conducted, but in order for the values encountered to be under the 0.9 threshold (Henseler et al., 2015), the construct AT1-A had to be removed for the EHEV dataset and the construct AT5-B had to be removed from the EBEV dataset. HTMT values are presented in tables 7 and 8 for EHEV and EBEV, respectively.

Table 5 - EHEV Fornell-Larcker Criterion

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 Behaviour Control, PEU = Perceived Ease-Of-Use, PU = Perceived Usefulness, SN = Subjective Norms, TTF = Task-Technology Fit

Table 6 - EBEV Fornell-Larcker Criterion

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 Behaviour Control, PEU = Perceived Ease-Of-Use, PU = Perceived Usefulness, SN = Subjective Norms, TTF = Task-Technology Fit

Table 7 - EHEV Heterotrait-monotrait

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 Behaviour Control, PEU = Perceived Ease-Of-Use, PU = Perceived Usefulness, SN = Subjective Norms, TTF = Task-Technology Fit

Table 8 - EBEV Heterotrait-monotrait

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 Behaviour Control, PEU = Perceived Ease-Of-Use, PU = Perceived Usefulness, SN = Subjective Norms, TTF = Task-Technology Fit

5.2. Structural Model and Hypothesis

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 5,000 resampling method iterations (Hair et al., 2021). The model analysis was also done separately for EHEV (or A) and EBEV (or B), as seen on figures 3 and 4 respectively.

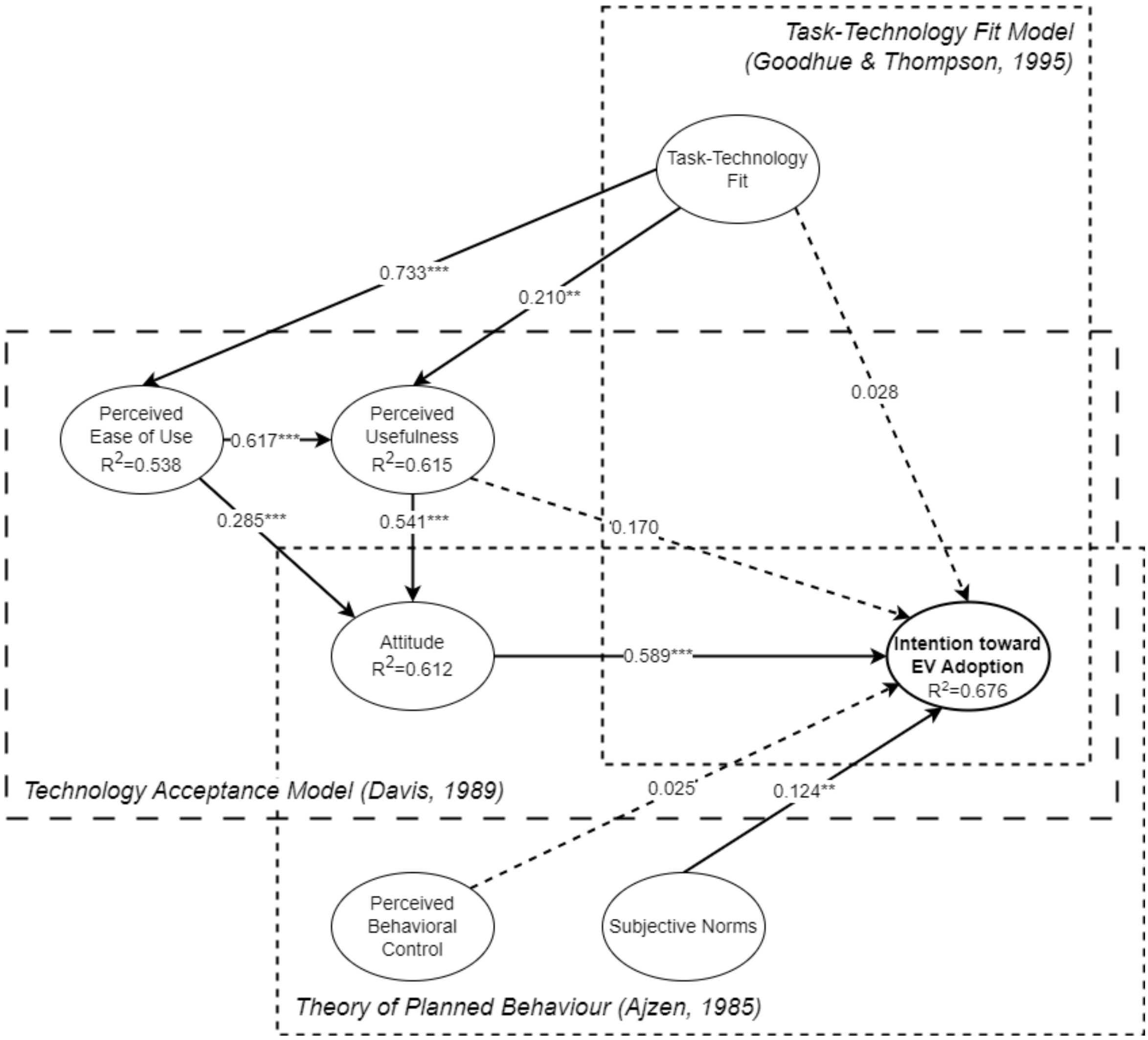

Figure 3 - EHEV supported hypothesis and statistical significance. Note: *p<0.1; **p<0.05; ***p<0.01

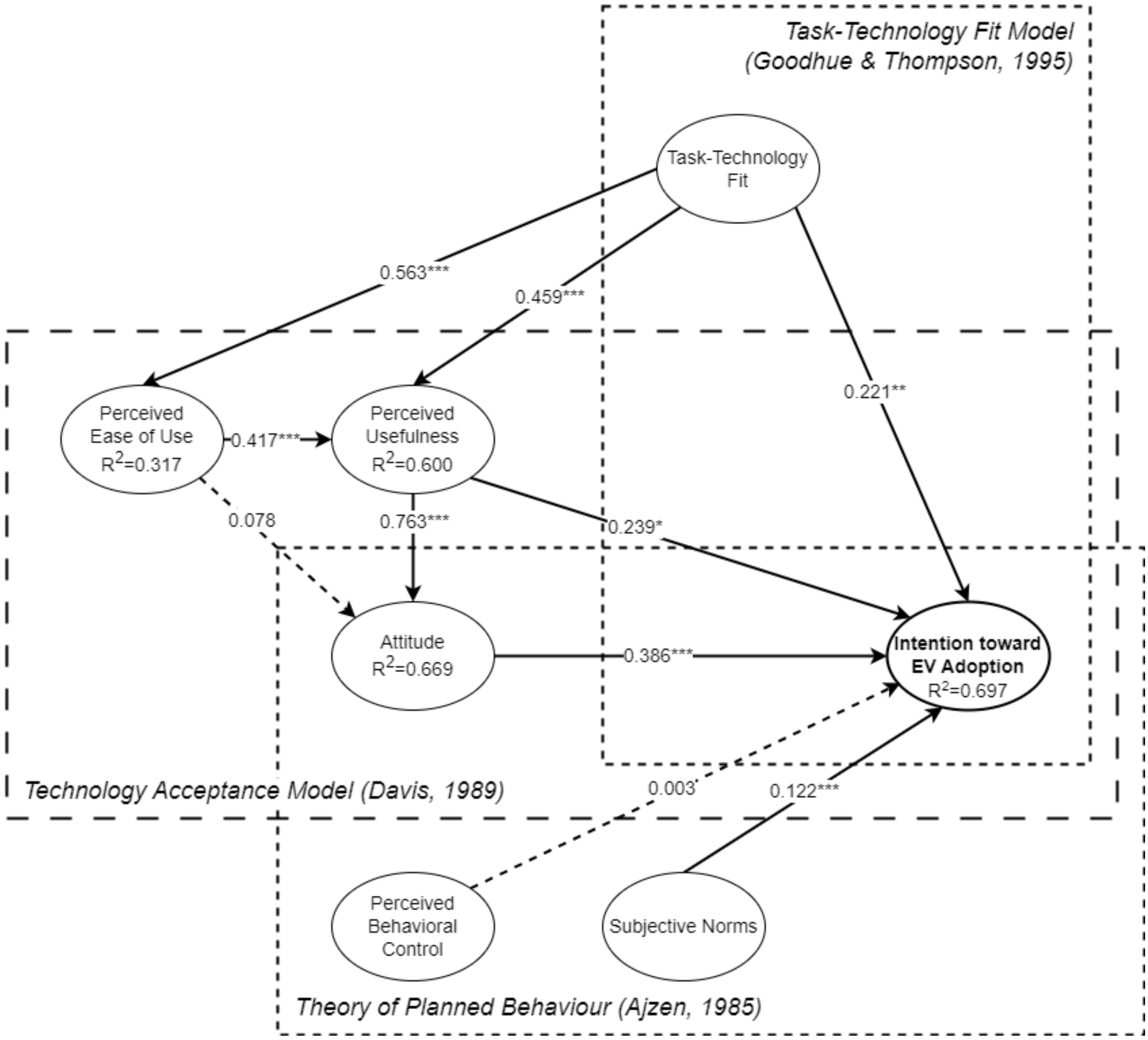

Figure 4 - EBEV supported hypothesis and statistical significance. Note: *p<0.1; **p<0.05; ***p<0.01

During 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 (Hair et al., 2021; Kock et al., 2012). 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 (Hair et al., 2021; Kock et al., 2012). Supported and rejected hypothesis are organized in tables 9 and 10 for EHEV and EBEV, respectively.

Table 9 - EHEV Supported and Rejected Hypothesis

Hypothesis		**Supported/ Rejected**	**Path Coefficient**	**Significance level (p)**
H1a	The Task-Technology Fit will have a positive impact on the perceived usefulness of the feature for EHEV with onboarded CEMG	Supported	0.210	0.026**
H2a	The Task-Technology Fit will have a positive impact on the perceived ease of use of the feature for EHEV with onboarded CEMG	Supported	0.733	0.000

Hypothesis		Supported/ Rejected	Path Coefficient	Significance level (p)
H3a	The Task-Technology Fit will have a positive impact on the intention of adoption of EHEV with onboarded CEMG	Rejected	0.028	0.676
H4a	The perceived ease of use will have a positive impact on the perceived usefulness of the feature for EHEV with onboarded CEMG	Supported	0.617	0.000***
H5a	The perceived ease of use will have a positive impact on the attitude towards EHEV with onboarded CEMG	Supported	0.285	0.000***
H6a	The perceived usefulness will have a positive impact on the attitude towards EHEV with onboarded CEMG	Supported	0.541	0.000***
H7a	The perceived usefulness will have a positive impact on the intention of adoption of EHEV with onboarded CEMG	Rejected	0.170	0.147
H8a	The attitude towards EVs will have a positive impact on the intention of adoption of EHEV with onboarded CEMG	Supported	0.589	0.000***
H9a	The perceived behavioural control will have a positive impact on the intention of adoption of EHEV with onboarded CEMG	Rejected	0.025	0.770
H10a	The subjective norm will have a positive impact on the intention of adoption of EHEV with onboarded CEMG	Supported	0.124	0.020**

*Legend: *p<0.1; **p<0.05; ***p<0.01*

Table 10 - EBEV Supported and Rejected Hypothesis

Hypothesis		Supported/ Rejected	Path Coefficient	Significance level (p)
H1b	The Task-Technology Fit will have a positive impact on the perceived usefulness of the feature for EBEV with onboarded CEMG	Supported	0.459	0.000***
H2b	The Task-Technology Fit will have a positive impact on the perceived ease of use of the feature for EBEV with onboarded CEMG	Supported	0.563	0.000***
H3b	The Task-Technology Fit will have a positive impact on the intention of adoption of EBEV with onboarded CEMG	Supported	0.221	0.006***
H4b	The perceived ease of use will have a positive impact on the perceived usefulness of the feature for EBEV with onboarded CEMG	Supported	0.417	0.000***
H5b	The perceived ease of use will have a positive impact on the attitude towards EBEV with onboarded CEMG	Rejected	0.078	0.225
H6b	The perceived usefulness will have a positive impact on the attitude towards EBEV with onboarded CEMG	Supported	0.763	0.000***

Hypothesis		Supported/ Rejected	Path Coefficient	Significance level (p)
H7b	The perceived usefulness will have a positive impact on the intention of adoption of EBEV with onboarded CEMG	Supported	0.239	0.050**
H8b	The attitude towards EVs will have a positive impact on the intention of adoption of EBEV with onboarded CEMG	Supported	0.386	0.000***
H9b	The perceived behavioural control will have a positive impact on the intention of adoption of EBEV with onboarded CEMG	Rejected	0.003	0.963
H10b	The subjective norm will have s a positive impact on the intention of adoption of EBEV with onboarded CEMG	Supported	0.122	0.009***

*Legend: *p<0.1; **p<0.05; ***p<0.01*

6. DISCUSSION

Among the findings provided by this study, the coefficient of determination values related with 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% (Liang et al., 2013), 65,5% (Kim et al., 2010), and 84,0% (Dishaw & Strong, 1999). Comparing the results of both vehicle groups, EHEV and EBEV, it is visible that some of the raised hypothesis can be supported or rejected based on what vehicle group it is tested against the model. The hypothesis H3(a, b), which assesses the impact of TTF of EVs 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 EVs 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) were both rejected meaning that it can be stated that the perceived usefulness and the perceived behaviour control on EVs onboarded with the CEMG feature is disassociated with the intention of adoption of EVs.

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 the 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 EBEVs as a more critical factor in their adoption decisions compared to EHEVs, 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 usability of the technology, which aligns with previous research that emphasizes the importance of ease of use in technology adoption (Cruz-Jesus et al., 2023; Dishaw & Strong, 1999).

Perceived usefulness was 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 (Dishaw & Strong, 1999; Irawan et al., 2022). This finding aligns with the TAM, where perceived usefulness is a key determinant of attitude and, subsequently, intention to adopt (Davis, 1989). 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, as perceived usefulness is typically considered a strong predictor of adoption intention (Schuitema et al., 2013), although pieces of literature also have previously failed to establish this impact (Dishaw & Strong, 1999; Irawan et al., 2022). 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 previous literature (Axsen & Kurani, 2009; Schuitema et al., 2013).

Perceived ease of use was shown to influence attitude towards the EVs 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 EHEVs, it does not play a similar role for EBEVs. 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 (Pamidimukkala et al., 2025), particularly when it comes to new or innovative technologies (Ajzen & Fishbein, 1980).

Perceived behavioural control did not have a significant effect on Intention to Adopt in either vehicle group, rejecting H9(a, b). This is consistent with 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 (Encarnação et al., 2018; Liang et al., 2013), although there are also previous literature supporting the correlation between PBC and intention of adoption (Irawan et al., 2022; Pamidimukkala et al., 2025).

6.1. Theoretical Implications

This study contributes to the body of knowledge with an innovative model, not yet tested in previous literature, by combining the Task-Technology Fit with Technology Acceptance Model and Theory of Planned Behaviour. 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 behaviour 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.

6.2. Practical Implications

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 personalized recommendations on driving habits that minimize CO2 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 impact positively EV adoption.

Since consumer adoption is influenced by perceived benefits, manufacturers should focus on educating the public on how CEMG enables users to lower CO2 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 behaviours 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 CO2 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 CO2 tracking, allowing them to optimize routes and fleet efficiency while demonstrating corporate sustainability efforts.

One of the most critical takeaways from this study is the power of information and perception. While tools like the 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 how effectively it is communicated, marketed, and integrated into the driver's experience.

6.3. Limitations and Future Research

While the study offers valuable insights, it is not without limitations. The sample may not fully represent the diversity of consumers across different regions, which could limit the generalizability of the findings. Future research could expand the sample size and explore how different demographic parameters affect adoption factors and decisions. Longitudinal studies could also be valuable in tracking changes in consumer attitudes and adoption behaviours over time as the EV market matures. 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. The impact of integrated CEMG with Smart Cities implementation could be an interesting topic and as features become more interconnected, understanding privacy and legal impacts on individual behaviour and perceived data safety becomes critical.

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 driving habits. Another interesting topic that could not be assessed in this research is the impact of CEMG in FFVs based on hydrogen power cells. Understanding adoption of this new technology could generate valuable new insights into sustainability in the automotive sector. Understanding how EVs onboarded with CEMG would respond as constructs of other models focused on assessing adoption of technology or individual behaviour could further test the validity of using TTF, TAM and TPB models together as an interesting multi-level acceptance model.

7. CONCLUSION

The transition toward sustainable transportation is no longer a distant vision, it is an urgent necessity. As climate change accelerates and urban air pollution worsens, reducing carbon emissions in the mobility sector has become a fundamental pillar of global sustainability efforts. Transportation accounts for a significant share of greenhouse gas emissions, and while policymakers, industry leaders, and consumers recognize the need for change, the path to a greener future remains complex.

Our study explored the key factors influencing the intention of adoption of EBEVs and EHEVs, emphasizing the role of task-technology fit, subjective norms, perceived behaviour control, perceived ease-of-use, perceived usefulness, and attitude towards electric vehicles. Task-technology fit encompassing how the CEMG observability feature proposed is perceived by consumers. Subjective norms threaded through constructs approaching how consumers are influenced by others around them, while perceived behaviour control reflected how their notion of control over a topic affects their individual behaviour. Perceived ease-of-use revolving around the perceptions of the consumer regarding how easy the observability feature is to use, perceived usefulness focusing on how useful consumer deem the CEMG to be and attitude being how consumers feel and see electric vehicles overall. The role of subjective norms and attitude towards electric vehicle have been supported as imperative drivers of intention of adoption both for EHEV and EHEV groups. The impact of perceived behaviour control was rejected as a direct driver in both groups as well. Task-technology fit and perceived usefulness presented positive impact on the intention of adoption of EBEV while for EHEV their impact was not supported. When considering indirect impact, for both vehicle groups, perceived ease-of-use had its positive impact supported on perceived usefulness, and perceived usefulness' impact supported against attitude, while perceived ease-of-use was proven impactful on attitude towards electric vehicles for the EHEV group, but not for the EBEV one.

The findings underscore that while technological advancements in fuel efficiency and CO2 emission management, such as the CEMG, play a crucial role in consumer decision-making, they must be complemented by strong behavioural, social, and economic incentives to drive large-scale adoption. Ultimately, the widespread adoption of EBEVs and EHEVs is a promising solution but requires a collaborative effort between governments, industry leaders, and consumers. By leveraging technological innovation, behavioural insights, and strategic policymaking, we can pave the way for a transportation ecosystem that is not only efficient and intelligent but also genuinely sustainable for future generations.

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APPENDICES

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	(Cruz-Jesus et al., 2023)
	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	(Kim et al., 2010)
	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	(Roemer & Henseler, 2022)
	PEU2	My interactions with an EHEV/EBEV with an onboarded CEMG is easy for me to understand	(Davis, 1989)
	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	(Dishaw & Strong, 1999)
	PEU5	Being an onboarded feature, the CEMG makes it easier for me to use the EHEV/EBEV	(Irawan et al., 2022)
Perceived Usefulness	PU1	The advantages of using an EHEV/EBEV with an onboarded CEMG (will) outweigh the disadvantages	(Roemer & Henseler, 2022)
	PU2	Overall, using an EHEV/EBEV with an onboarded CEMG is useful	(Irawan et al., 2022)
	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	(Barbarossa et al., 2015)
	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	(Kim et al., 2010)
	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	(Jansson et al., 2017)
	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	
Perceived Behavioural	PBC1	I am in full control of using an EHEV/EBEV with an onboarded CEMG to understand my emission reduction	(Liang et al., 2013)

Construct	Item	Adaption	Source
Control	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	(Barbarossa et al., 2015)
	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	(Degirmenci & Breitner, 2017)
	IA4	Given that I had the opportunity, I predict that I would buy an EHEV/EBEV with an onboarded CEMG	

Appendix B. Demographic characteristics of the respondents

Characteristics	**Frequency (n = 137)**	
	N	**%**
Gender		
Male	68	49.6
Female	69	50.4
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
> 65	5	3.65
Education Level		
Secondary Level Graduate	7	5.11
College Graduate	92	67.15
Master	32	23.36
Doctorate	4	2.92
Prefer not to state	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
Disabled	1	0.73
Prefer not to state	7	5.11

Appendix C. EHEV loadings and cross-loadings

	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
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 D. EBEV loadings and cross-loadings

	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

	AT	IA	PBC	PEU	PU	SN	TTF
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**

Appendix E. Ethics Committee Report

This is to certify that

Project No.: **INFSYS2025-3-112253**

Project Title: **Understanding the Determinants of Sustainability and Adoption on the Automotive Sector - Private sector influence on drivers of adoption and consumption of electric vehicles**

Principal Researcher: **Vitor Figueiredo**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal

Review Board, being considered **APPROVED** on 3/11/2025.

It is the Principal Researcher’s responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of
- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 3/11/2025

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