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Analysis of car consumers' needs: consumption model and preferences among internal combustion, hybrid and electric vehicles

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ABSTRACT

In recent years, the automotive sector has undergone a profound transformation driven by two converging forces: technological progress and increasing environmental pressure. The diffusion of electric vehicles (EVs) and hybrid electric vehicles (HEVs), supported by public policies and industrial investments, represents one of the main strategies to reduce greenhouse gas emissions and promote more sustainable mobility. However, the adoption of these technologies by consumers is not automatic, but depends on a variety of psychological, social and economic factors that shape perception and purchase intention. Within this context, the present study aims to investigate the behaviour of Italian consumers regarding the adoption of low-emission vehicles.

The thesis is structured into eight chapters. The first is an introductory chapter, which defines the context, the relevance of the topic and the research objectives. This is followed by a methodological chapter that describes the approach adopted, the operational phases and the tools used to carry out the research.

Chapter 3 provides an overview of the main theoretical models of technology acceptance, with a focus on the Technology Acceptance Model (TAM), UTAUT2 and its extensions. It also introduces the concept of customer experience and its growing role in consumption decisions.

Chapter 4 applies these models to the automotive sector, highlighting the specificities of the Italian market and the main drivers influencing the choice between electric, hybrid and traditional vehicles. The following chapters focus on the development of an original theoretical model and its empirical validation.

The methodological core of the thesis is presented in Chapter 5, which proposes a streamlined conceptual framework articulated into four key constructs: Technology Appraisal, Socio-Environmental Influence, Consumer Experience Engagement and Perceived Value. The model was operationalised through a structured Likert-scale questionnaire, administered to a representative sample of the Italian population in terms of gender, age and educational level.

Chapter 6 presents the statistical analysis of the collected data (N=364), structured in multiple phases: descriptive analysis, item reliability assessment, exploratory factor analysis, ANOVA by vehicle type, multiple regression and finally, structural equation modelling (SEM). The results show that all independent variables significantly influence intention and usage behaviour, with substantial differences across user groups. Notably, Technology Appraisal emerged as the most predictive dimension, followed by Consumer Experience Engagement. Socio-Environmental Influence had a stronger impact among younger individuals and those with greater environmental awareness, while Perceived Value was more influential among participants with lower incomes or limited driving experience.

Chapter 7 provides a critical discussion of the results, comparing them with previous studies and reflecting on practical and theoretical implications. Particular emphasis is placed on the importance of customised communication strategies and policies, tailored to different consumer segments.

Chapter 8 opens with a general conclusion. The chapter also discusses the study's limitations, such as the simplification of the model and the difficulty in clearly distinguishing between electric and hybrid vehicles in participants' perceptions. Finally, it outlines several directions for future research, including the integration of qualitative variables, longitudinal analysis and field experiments.

The thesis also includes sections dedicated to the project's timeline and overall budget, the assessment of the main social, economic and environmental impacts, the analysis of legal and ethical aspects related to the work carried out and the potential contribution to the Sustainable Development Goals (SDGs) promoted by the United Nations.

Overall, this thesis offers both a theoretical and practical contribution to understanding the processes governing the adoption of new sustainable technologies, providing useful insights for automotive companies, policymakers and researchers interested in the intersection of innovation, environment and consumer behaviour.

Keywords: acceptance models, automotive, consumer behaviour, customer experience, electric and hybrid vehicles, environmental policy, SEM, sustainable mobility, technology adoption.

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1. INTRODUCTION: CONTEXT AND OBJECTIVES

In recent years, the transition towards sustainable mobility has taken on a central role in public discourse, driven by the growing urgency to reduce pollutant emissions, the advancement of green technologies and the goals set at the European level regarding decarbonisation. Within this context, the adoption of electric and hybrid vehicles represents one of the most complex and strategic challenges for the automotive sector, not only for its environmental and economic implications but also due to the need to fully understand the psychological, social and cultural mechanisms that shape consumer behaviour.

The relevance of this topic is especially significant in the Italian context, where internal combustion engine vehicles still dominate, despite recent progress in charging infrastructure and public incentives. The slow adoption of low-emission vehicles in Italy raises fundamental questions about the effectiveness of current policies, as well as the subjective perception of technology, consumer trust and the influence of experiential and value-based factors.

In light of these premises, the **objective** of this thesis is to analyse the factors that influence Italian consumers' intention and behaviour regarding the adoption of electric and hybrid vehicles. The aim is to construct a theoretical and empirical model that integrates the main contributions of technology acceptance models (in particular UTAUT2) with variables related to customer experience and personal and social sustainability, in order to provide a multidimensional and realistic understanding of the phenomenon.

Starting from this general objective, the research is guided by the following **research questions**:

1. What are the main factors, technological, experiential, social and economic, that influence the intention to adopt an electric or hybrid vehicle in Italy?
2. To what extent do these factors vary according to the consumer's sociodemographic characteristics (age, gender, residence, income, education, driving experience)?
3. What are the main interdependencies among the constructs involved in the decision-making process?
4. How do perceptions and attitudes differ between users of electric, hybrid and internal combustion vehicles?

To address these questions, a set of **research hypotheses** has been formulated, linking the four independent macro-variables of the proposed model (Technology Appraisal, Socio-Environmental Influence, Consumer Experience Engagement and Perceived Value) to adoption intention, while also exploring the moderating effect of sociodemographic variables.

The thesis therefore aims to contribute to the scientific and practical debate on sustainable mobility, offering useful evidence for companies, policymakers and researchers interested in understanding and supporting behavioural change in the Italian automotive sector.

2. METHODOLOGY

This thesis adopts a **quantitative deductive methodology**, based on the integration of a solid theoretical framework with the empirical analysis of data collected through a structured questionnaire. Following an in-depth literature review on technology acceptance models and customer experience, an original conceptual model was developed, synthesizing and integrating the main factors identified in the literature into four latent macro-variables. Based on this framework, a behavioural questionnaire was constructed and administered to a sample of individuals representative of the Italian population with respect to key sociodemographic variables (age, gender, educational level).

The **data collection** was followed by a rigorous phase of cleaning, coding and validation, which preceded a multi-step **statistical analysis**: reliability analysis (Cronbach's alpha), descriptive statistics, analysis of variance (ANOVA), linear regressions and finally, modelling through SEM (Structural Equation Modeling), with the aim of testing the hypotheses and the relationships among constructs. All analyses were carried out using the R software, in line with best practices in applied social research. The research design also included a segmentation of usage behaviour into three categories (electric, hybrid, internal combustion), in order to capture differences across user groups.

3. THEORETICAL FRAMEWORK: THECNOLOGY ACCEPTANCE MODELS AND CONSUMER BEHAVIOUR

In recent decades, the acceleration of technological progress has made the study of technology acceptance and adoption by individuals increasingly relevant. In a context where innovation affects not only industrial processes but also the everyday lives of consumers, it becomes essential to understand the psychological, cognitive and social mechanisms that guide decisions to use new technological solutions. In particular, within the field of mobility and the automotive industry, the growing diffusion of electric and hybrid vehicles represents one of the main challenges and opportunities of the ongoing ecological transition. However, technological availability alone does not guarantee its acceptance: consumer behaviour, perceptions, beliefs and attitudes play a crucial role.

Since the 1980s, several **theoretical models** have been developed to explain how users accept new technologies. The most prominent include the Technology Acceptance Model (TAM) and its extensions, the Unified Theory of Acceptance and Use of Technology (UTAUT), the Theory of Planned Behaviour (TPB), the Norm Activation Model (NAM) and Rogers' Diffusion of Innovations Theory. These models are based on variables that aim to capture behavioural intention and the psychological, social and environmental determinants that influence its formation. Some approaches highlight the importance of perceived usefulness and ease of use, while others focus on the role of social norms, perceived control, or moral beliefs. The variety of these models reflects the complexity of decision-making processes related to technology adoption, which are expressed through purchasing, usage and diffusion behaviours.

At the same time, a perspective has emerged that integrates technology acceptance theory with developments in consumer theory, particularly through the experiential approach. In this view, the consumer is not merely a rational agent who weighs costs and benefits, but also a subject who creates value through experiences, emotions, relationships and symbols. The concept of customer experience has gradually assumed a central role in understanding contemporary consumer behaviour, especially in high-involvement sectors such as the automotive industry.

This chapter aims to critically and systematically reconstruct the main models of technology acceptance and consumer experience. Their key variables, application contexts and theoretical limitations will be examined, with the objective of providing an integrated conceptual framework to be applied in the following chapter to the analysis of consumer behaviour in the automotive sector.

3.1. TECHNOLOGY ACCEPTANCE MODELS (TAM)

The **Technology Acceptance Model (TAM)**, proposed by Fred Davis in 1986, was developed as an adaptation of the Theory of Reasoned Action (Ajzen & Fishbein, 1980) to the technological context and represents one of the most established and widely used models for explaining individual technology acceptance and use [Figure 1]. The main objective of TAM is to explain and predict the factors that lead an individual to accept and adopt a new technology.

According to the model, consumer behaviour is determined by a sequence of interdependent variables. At the foundation are **external variables**, **the system** and **user-independent characteristics** that can influence individual perceptions. Examples include the presence of government incentives, prior technological experience, product design quality, or the existence of supporting infrastructure (e.g., electric vehicle charging stations).

These external variables affect two central perceptual constructs:

- **Perceived Usefulness**: the degree to which a person believes that using the technology will enhance their performance or efficiency. In the automotive context, this could refer to fuel savings, the convenience of home charging, or access to low-emission zones.
- **Perceived Ease of Use**: the degree to which a person believes that using the technology will be free of effort. For an electric vehicle buyer, this may relate to the intuitiveness of digital features, simplicity of the charging process, or ease of maintenance.

Both variables influence the individual's A**ttitude Toward Use,** which in turn shapes their **Behavioural Intention**, a direct predictor of **Actual System Use**. Moreover, Perceived Ease of Use also affects Perceived Usefulness, as a simpler technology is often viewed as more beneficial.

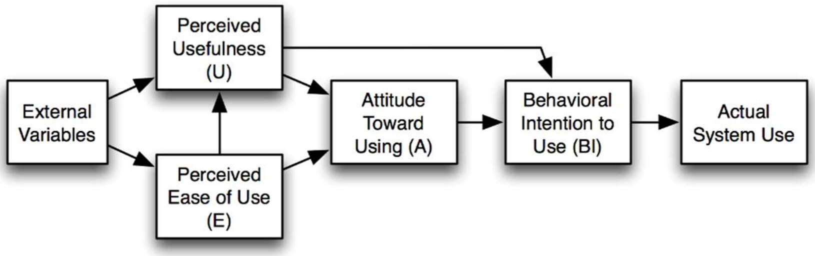

Figure 1: Technology Acceptance Model (TAM) with external, perceptual, attitudinal and behavioural variables. Source: Technology acceptance model – Wikipedia.

TAM has been successfully applied across many fields, from business information systems to mobile applications. In the automotive sector, its application is particularly relevant, as the introduction of electric vehicles (EVs) represents a radical shift in consumer habits and perceptions.

3.1.1. LIMITATIONS OF THE TAM

Despite its widespread use and simplicity, the Technology Acceptance Model presents certain structural limitations that reduce its ability to fully capture the complexity of human behaviour, particularly in dynamic consumer contexts such as the automotive sector.

The first limitation concerns the **limited number of variables** included in the model: TAM focuses exclusively on Perceived Usefulness and Perceived Ease of Use, overlooking other psychological and social factors that influence behavioural intention, such as social norms, emotions, trust, or habits.

Secondly, TAM was originally developed for **organizational and work-related settings**, where technology adoption is aimed at improving productivity and often mandated from above. This reduces its ability to interpret voluntary and subjective decisions, such as the purchase of an electric vehicle, where symbolic, value-driven and emotional factors come into play.

Another limitation lies in the **static nature of the model**, which does not account for changing perceptions over time or the influence of accumulated experience with the technology.

Finally, the **absence of contextual or infrastructural variables** limits the model's applicability to complex scenarios where the external environment plays a crucial role, as is the case with electric mobility, where factors such as charging infrastructure, public incentives and local regulations significantly influence consumer behaviour.

3.2. EXTENSIONS OF THE TAM MODEL: TAM2 AND TAM3

With the evolution of technologies and changing consumer expectations, the TAM model has been enhanced through the integration of new variables, most notably with the development of **TAM2**, proposed by Venkatesh and Davis in 2000 and the subsequent **TAM3**, introduced in 2008 by Venkatesh and Bala [Figure 2].

TAM2 incorporates **social and cognitive variables** that influence Perceived Usefulness, such as:

- **Subjective Norm**: the perceived social pressure from significant others (e.g., friends, family, colleagues) regarding the use of a technology. In the case of electric cars, this may refer to the influence of others' opinions on the decision to adopt an EV.
- **Image**: the degree to which using the technology enhances one's social status.
- **Job Relevance**: the extent to which an individual believes that the technology is relevant to their personal or professional needs. In the automotive context, this could relate to whether the vehicle meets specific needs (e.g., urban commuting, long-distance travel, family use).
- **Output Quality**: the degree to which the technology delivers effective and satisfactory performance. A reliable, well-designed and technologically advanced vehicle positively contributes to this perception.
- **Result Demonstrability**: the ease with which the benefits of the technology can be observed, measured, or communicated. In the automotive context, this may refer to energy savings, cost reduction, or the quietness typical of electric driving.

These variables help explain how individuals assess whether a technology will improve their condition, both functionally and symbolically.

TAM3 provides a more in-depth analysis of the determinants of Perceived Ease of Use. It introduces the following cognitive and affective factors:

- **Computer Self-Efficacy**: the user's confidence in their ability to use the technology effectively, even without assistance. For electric vehicles, a high sense of self-efficacy means confidence in managing digital features (e.g., charging apps, infotainment systems) independently.

- **Perception of External Control**: the degree to which the user believes that adequate resources and support are available to use the technology effectively (e.g., availability of charging infrastructure and technical assistance).
- **Computer Anxiety**: the level of discomfort or apprehension one feels about using a technology. Consumers with high anxiety may avoid EVs due to fears of mishandling advanced systems or making mistakes while charging.
- **Computer Playfulness**: the user's spontaneous inclination to explore and interact with the technology in a creative way. Consumers with high playfulness may enjoy experimenting with the vehicle's digital systems (e.g., customizable displays, smart functions, assisted driving).
- **Perceived Enjoyment**: the extent to which using the technology is considered intrinsically enjoyable, regardless of practical outcomes, e.g., the quietness of electric driving or interaction with modern, intuitive interfaces.
- **Objective Usability**: the measurable ease with which a technology enables task completion, often based on tests or benchmarks. In EVs, this might be assessed through the ease of the charging process or user interface clarity.

While these factors may appear secondary, they are central in the context of unfamiliar or novel technologies, such as for first-time EV adopters or those new to digital interfaces.

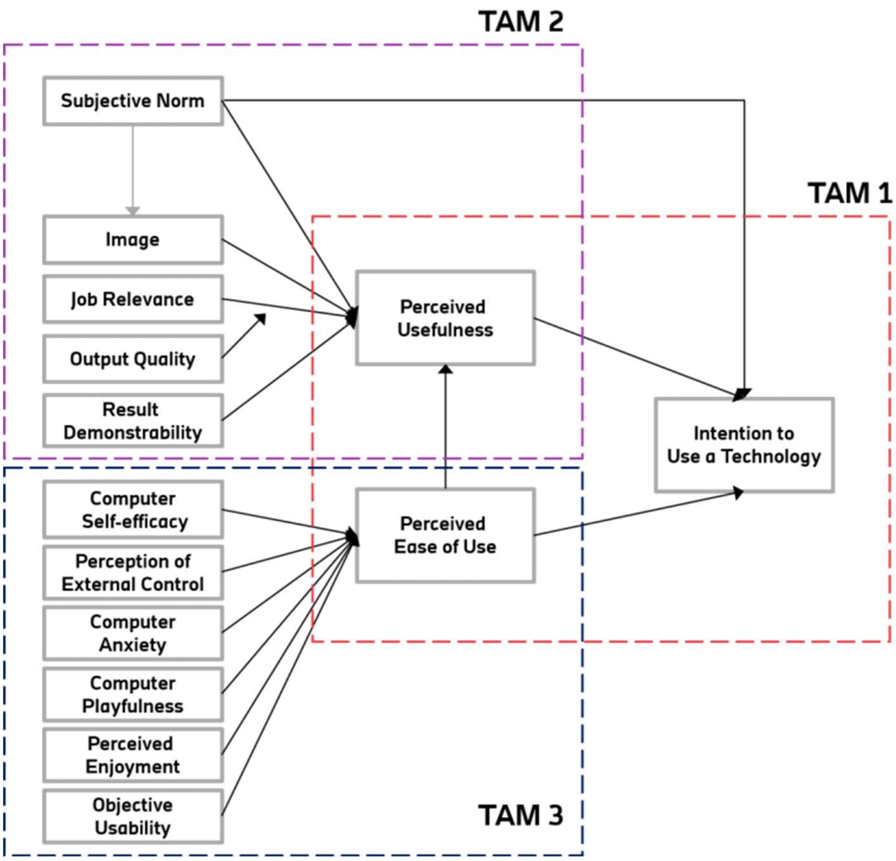

Figure 2: Comparison between TAM, TAM2 and TAM3. Source: Technology acceptance model TAM - Innovation Acceptance Lab.

Both **TAM2** and **TAM3** have been applied across a wide range of domains, including the adoption of enterprise software, web applications, digital banking services, mobile platforms and more recently, consumer technologies such as smart devices and connected cars. In the automotive sector, the introduction of electric vehicles, equipped with advanced digital interfaces and new modes of interaction, makes these extensions particularly well-suited to interpret consumer attitudes, especially during the initial stage of product engagement.

3.2.1. LIMITATIONS OF TAM2 AND TAM3

Despite being more elaborate than the original TAM, both **TAM2** and **TAM3** still present some notable limitations.

Regarding **TAM2**, the inclusion of numerous additional variables, such as Subjective Norm, Image, Job Relevance, or Output Quality, makes the model **more complex to apply empirically**, increasing the risk of conceptual overlap and operational difficulties in measuring the constructs.

A second limitation lies in the model's failure to incorporate **emotional and value-driven dimensions**: although it introduces social influence, TAM2 remains anchored in a predominantly utilitarian and cognitive logic, overlooking aspects related to intrinsic motivation, sustainability, or personal identity. This limits its effectiveness in consumer contexts where the symbolic meaning of technology plays an important role, such as in the choice of an electric vehicle.

Finally, TAM2 maintains an **individualistic and decontextualized perspective**, which does not adequately consider external, infrastructural, regulatory, or cultural conditions that affect technology adoption. This may reduce its explanatory capacity in sectors such as automotive, where the presence or absence of external support mechanisms (e.g., charging stations, financial incentives) significantly shapes purchasing decisions.

Turning to **TAM3**, the model introduces a large number of cognitive and affective variables (e.g., self-efficacy, external control, anxiety, playfulness, enjoyment, objective usability), which can make the empirical measurement phase **complex** and burdensome, particularly when working with small sample sizes or standardized survey instruments.

Moreover, many of the variables added in TAM3, although theoretically valuable, are **strongly linked to the individual level of interaction** with technology and may be less relevant in complex consumer contexts such as the automotive sector, where social, cultural and systemic factors also come into play. In this sense, TAM3 maintains a partial view focused on the expert user, which may not accurately represent the full spectrum of consumers.

Lastly, the model continues to overlook **ethical, social and environmental motivations**, as well as the impact of the overall user experience (customer experience) and external conditions. This makes it less suitable for contexts in which technology adoption is driven not only by efficiency and ease of use, but also by personal convictions, group dynamics, or environmental context factors.

3.3. UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY (UTAUT AND UTAUT2)

Building on TAM, TAM2 and other prior frameworks, Venkatesh and colleagues introduced the **Unified Theory of Acceptance and Use of Technology (UTAUT)** in 2003 [Figure 3]. This model synthesizes the key variables identified in the literature and aims to provide a more comprehensive and predictive understanding of technology adoption.

UTAUT is based on four core constructs:

- **Performance Expectancy**: comparable to perceived usefulness, it refers to the degree to which using the technology is expected to enhance performance.
- **Effort Expectancy**: analogous to perceived ease of use, it refers to the expected ease associated with using the technology**.**
- **Social Influence**: the extent to which individuals perceive that important others believe they should use the technology.
- **Facilitating Conditions**: the degree to which the environment (infrastructure, technical support, system compatibility) supports the use of the technology.

These constructs are moderated by demographic variables such as **age**, **gender**, **experience** and **voluntariness of use**. For example, a younger, tech-savvy adult may place greater emphasis on performance and be less concerned with usability, while an older individual might have the opposite attitude.

In the context of electric vehicles, the UTAUT model helps explain why some consumers quickly adopt alternative vehicles while others remain sceptical. Variables such as the availability of charging stations (Facilitating Conditions), expectations of cost savings and performance (Performance Expectancy), or the perception that "everyone around me is buying one" (Social Influence) are all critical determinants.

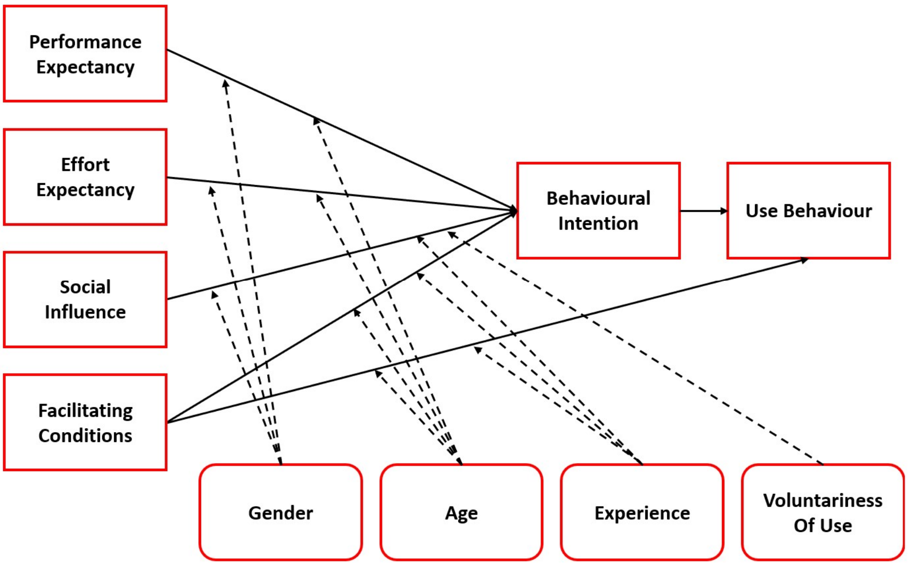

Figure 3: UTAUT: Unified Theory of Acceptance and Use of Technology. Source: Unified Theory UTAUT - Innovation Acceptance Lab.

In 2012, Venkatesh and colleagues proposed an updated version, **UTAUT2**, tailored to the context of individual consumer behaviour [Figure 4]. Compared to the original model, UTAUT2 adds three new variables:

- **Hedonic Motivation**: the fun or pleasure derived from using the technology.
- **Price Value**: the perceived trade-off between the benefits of the technology and its monetary cost.
- **Habit**: the degree to which behaviour is automatic or habitual.

These additions make the model more suitable for analysing consumer purchase decisions, where emotions, price and habits are just as important as functionality. For instance, a buyer might choose an electric vehicle not only to save money but also for the pleasure of a quiet driving experience, advanced onboard technology, or the satisfaction of contributing to a broader transformation.

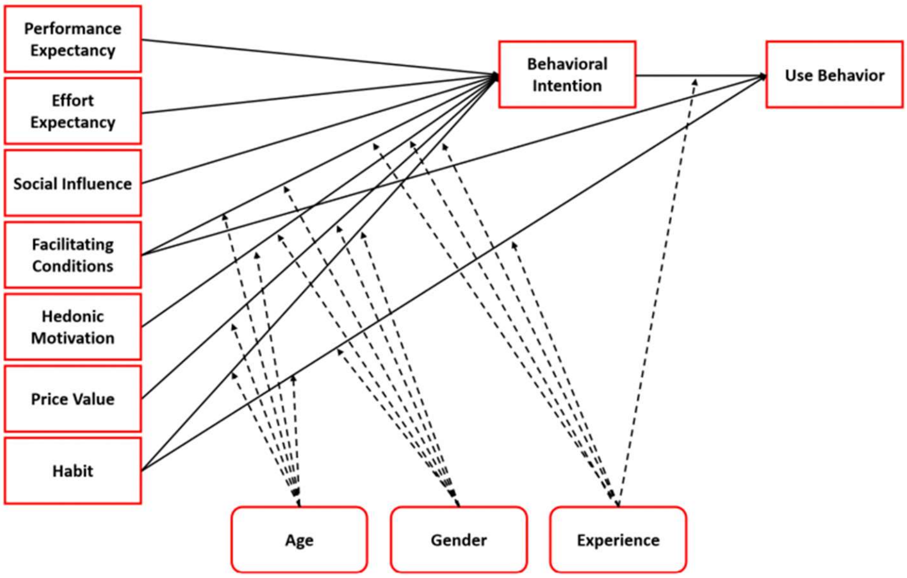

Figure 4: UTAUT2: extension to the consumer context. Source: Unified Theory UTAUT - Innovation Acceptance Lab.

UTAUT has been widely adopted to study the introduction of technologies in corporate, healthcare, educational and public settings, while **UTAUT2** has proven to be more suitable for personal consumption contexts, such as the use of mobile apps, online banking services, smart appliances and more recently, electric vehicles. In particular, the dimensions of Hedonic Motivation and Habit have emerged as crucial in understanding purchasing dynamics in the automotive sector, where emotion, status and lifestyle are just as influential as functional utility.

3.3.1. LIMITATIONS OF UTAUT AND UTAUT2

Despite its conceptual breadth and the intention to integrate key preceding theories, **UTAUT** presents certain structural limitations that reduce its flexibility and adaptability to less standardized contexts.

First, the model was developed primarily for organizational and corporate environments, where technology adoption is often influenced by institutional constraints and work-related obligations. This limits its effectiveness in describing **free and voluntary consumer behaviours**, such as those that characterize the automotive market.

A second limitation concerns the **presence of multiple moderating variables** (age, gender, experience, voluntariness of use) which, while enriching the model, may excessively complicate its empirical application, especially in small or heterogeneous samples. Moreover, the influence of these moderators is not always stable across different cultural or technological contexts.

Finally, UTAUT maintains a **predominantly cognitive and rational structure**, focused on cost–benefit analysis and the evaluation of technological performance, overlooking affective, value-based, or symbolic elements that, as highlighted in Chapter 4, play a significant role in purchasing decisions related to sustainable mobility. This makes the model less suitable for capturing the emotional or identity-based dimensions that may drive a consumer to choose an electric vehicle over a traditional one.

Even the extended version, **UTAUT2**, although it improves the explanatory power of the original model and is better suited to the context of individual consumption, presents some critical issues that should be considered.

First, the addition of new variables such as **Hedonic Motivation**, **Price Value** and **Habit** increases the complexity of the model and makes its practical application more difficult. Some studies have shown that these constructs, if not precisely measured, may conceptually overlap with existing ones, creating issues of ambiguous interpretation.

Second, although habit is a relevant behavioural component, it can become so dominant that it overshadows the influence of other, more cognitive or motivational variables. This may reduce the model's ability to explain **behavioural changes over time**, particularly in the early stages of technological diffusion.

Another limitation lies in the **absence of normative or value-based dimensions**, such as environmental awareness, social responsibility, or alignment with ethical principles, factors that are crucial in sustainable consumption choices. This makes UTAUT2 less suitable in contexts where technology adoption is driven not only by usefulness and pleasure, but also by moral or identity-based motivations, as is often the case with electric vehicle purchases.

Lastly, it is important to highlight the **context-dependency** of the new variables introduced: factors such as hedonic motivation or perceived price value can vary significantly depending on the type of technology, the industrial sector and the cultural setting. This underscores the need for careful adaptation of the model to the empirical context, in order to avoid distorted or non-generalizable interpretations.

3.4. THEORY OF REASONED ACTION (TRA)

The **Theory of Reasoned Action (TRA)**, proposed by Fishbein and Ajzen in 1975, is one of the earliest and most influential psychological models used to explain intentional human behaviour [Figure 5]. Originally developed within the field of social psychology and later extended to various applied contexts, the theory is based on the assumption that individuals are rational agents who act deliberately, evaluating the consequences of their actions. According to this perspective, behaviour is not random or impulsive, but rather the result of a conscious intention, influenced by personal beliefs and perceived social pressure.

The model is built around **two key variables** that determine Behavioural Intention, considered the primary predictor of **Actual Behaviour**:

- **Attitude Toward the Behaviour**: this refers to the overall positive or negative evaluation that an individual attributes to performing a given action. For example, a favourable attitude toward using an electric vehicle may stem from the perception that it is eco-friendly, modern, or economically advantageous.
- **Subjective Norm**: this reflects perceived social pressure, i.e., the extent to which the individual believes that significant others (family, friends, colleagues) expect them to perform a certain behaviour. In the automotive domain, this variable may be influential if, for instance, one's peer group values the choice of an electric vehicle as a symbol of environmental responsibility or technological status.

These two components influence **Behavioural Intention**, which in turn predicts A**ctual Behaviour**, provided the individual has actual control over their actions. However, as will be further discussed in the TPB (next section), this aspect is later refined.

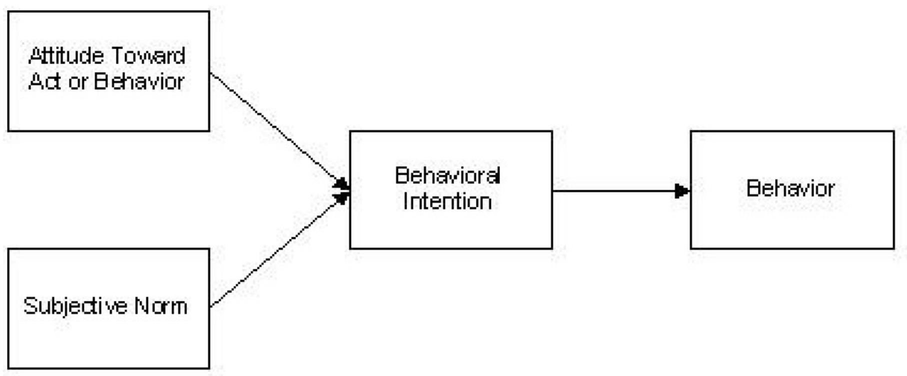

Figure 5: Model of the Theory of Reasoned Action (TRA). Source: Fishbein & Ajzen (1975).

TRA has been widely applied in social, educational and marketing contexts to understand a broad range of behaviours: from adopting healthy habits (e.g., quitting smoking) to making purchasing decisions for new products. In the field of technology, it served as the theoretical foundation for the Technology Acceptance Model (TAM) and is still used today to analyse responsible consumer choices, such as the adoption of electric or sustainable vehicles. The model is particularly useful in contexts where behaviour results from conscious deliberation and is not strongly constrained by external factors.

3.4.1. LIMITATIONS OF THE TRA

Due to its simplicity, **TRA** has certain limitations that reduce its applicability in more complex scenarios.

The primary issue lies in the assumption that all behaviour is entirely under the **individual's control**. In reality, many choices, such as the purchase of an electric vehicle, may be influenced by practical constraints, such as price, the availability of charging infrastructure, or public policies, which are not accounted for in the TRA.

Moreover, the model does not incorporate **affective, habitual, or contextual dimensions**, which can influence behaviour independently of intention. Finally, although TRA includes social influence through the Subjective Norm, it does not distinguish between **normative**, **informational**, or **symbolic** influences, elements that are better articulated in more advanced models such as TPB or UTAUT.

3.5. THEORY OF PLANNED BEHAVIOUR (TPB)

The **Theory of Planned Behaviour (TPB)**, developed by Icek Ajzen in 1991 as an extension of the Theory of Reasoned Action (TRA), was designed to overcome its limitations by introducing a key element: perceived behavioural control [Figure 6]. The idea underlying TPB is that an individual's intention to perform a given action depends not only on personal attitude and social influence, but also on the perception of having (or lacking) the resources and abilities necessary to carry it out. This extension made the model particularly suitable for analysing behaviours that are not entirely voluntary, as is often the case in technological or sustainable consumption choices.

TPB is structured around three central variables that directly influence **Behavioural Intention**:

- **Attitude Toward the Behaviour**: this refers to the overall evaluation that an individual attributes to a specific action, based on expected outcomes and the value assigned to those outcomes. A positive attitude toward adopting an electric vehicle, for instance, may stem from the belief that it brings environmental, economic, or image-related benefits.

- **Subjective Norm**: this reflects perceived social influence, i.e., the judgment or pressure exerted by significant others regarding a particular behaviour. In the context of sustainable mobility, the subjective norm may take the form of a desire to conform to family, peer, or workplace expectations.
- **Perceived Behavioural Control**: this is the core innovation of the model and refers to the individual's perception of the ease or difficulty of performing the behaviour. It is shaped by external barriers (such as the cost of an electric vehicle or the lack of charging stations) and internal factors (such as technical skills or personal confidence in managing the new technology).

Behavioural Intention is considered the best predictor of **Actual Behaviour**, although in TPB, actual behaviour can also be directly influenced by Perceived Control, acknowledging that in some cases, individuals may act only if they genuinely have the resources or opportunities to do so.

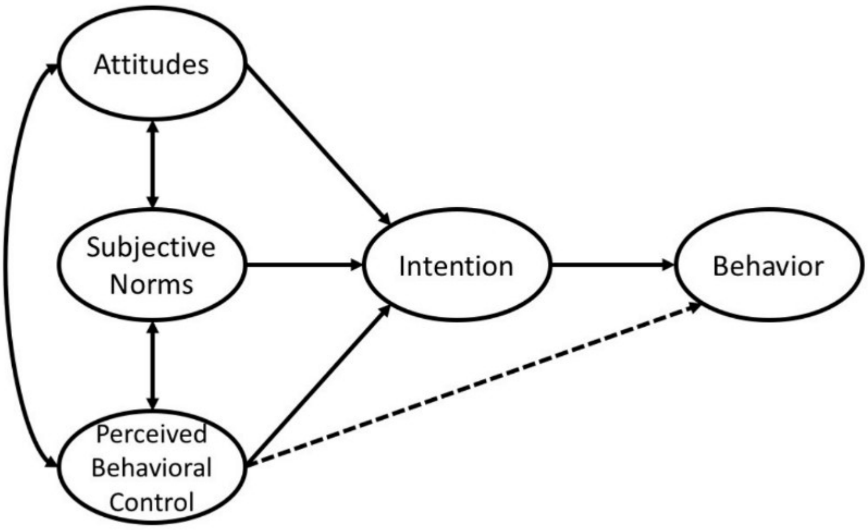

Figure 6: Model of the Theory of Planned Behaviour (TPB). Source: Ajzen (1991).

TPB has found broad application in social psychology, marketing, environmental studies and consumer behaviour research, thanks to its versatility and predictive power. It has been used to study behaviours related to health, sustainability, safety and innovation adoption. In the automotive context, it is particularly suitable for analysing the intention to purchase electric or hybrid vehicles, as it allows for the consideration of rational evaluations, social pressures and perceived barriers that may hinder the decision.

3.5.1. LIMITATIONS OF THE TPB

Although it is a robust evolution of the TRA, **TPB** presents some limitations that reduce its interpretative completeness.

First, it is based on **intentional and planned logic**, making it less effective in explaining impulsive, habitual, or emotion-driven behaviours. In addition, it does not include variables such as **personal morality** or **perceived price value**, which may play a significant role in many consumer decisions.

Another common critique relates to the **difficulty of accurately measuring** Perceived Behavioural Control, which may vary over time and between individuals and does not always correspond to objective conditions.

Finally, TPB is structurally **neutral** with respect to cultural or regulatory context, limiting its ability to capture deeper dynamics that influence the adoption of complex or sustainable technologies, such as in the case of electric mobility.

3.6. NORM ACTIVATION MODEL (NAM)

The **Norm Activation Model (NAM)**, proposed by Schwartz (1977), is a psychological model developed to explain prosocial behaviour and, more broadly, actions motivated by moral values [Figure 7]. Unlike rational models such as TAM or TPB, NAM focuses on ethical and internalized dynamics, placing at the centre the individual's perception of moral responsibility toward others and the environment. This makes it particularly suitable for interpreting behaviours in which individuals act not out of convenience or social pressure, but in accordance with what they believe is right.

The model is structured around three main variables:

- **Awareness of Consequences:** the awareness of the negative consequences that one's behaviour may have on others or on the environment. For example, being aware of the environmental impact of internal combustion engine vehicles.
- **Ascription of Responsibility**: the sense of personal responsibility for those consequences.
- **Personal Norms**: the internal moral rule that motivates the individual to act in a certain way, regardless of external obligations. It represents a subjective sense of duty, which

may lead to pro-environmental behaviour, such as choosing an electric vehicle, even in the absence of immediate economic benefits.

In NAM, the Personal Norm is "activated" when the individual is aware of the consequences of their behaviour and feels personally responsible for avoiding them. This triggers an **ethical impulse**, which can then translate into concrete action.

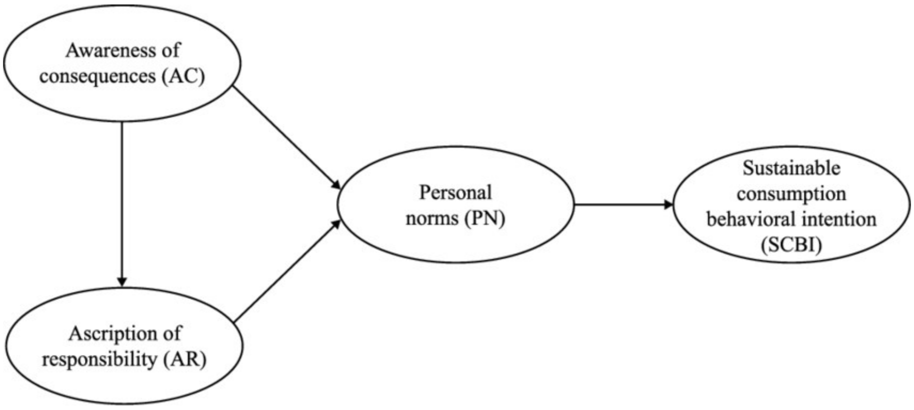

Figure 7: Model of the Norm Activation Model (NAM). Source: Schwartz (1977).

NAM was originally formulated to explain altruistic and solidarity-driven behaviour, but has been widely applied in environmental psychology, where it is used to understand the adoption of eco-friendly behaviours, from recycling and using public transportation to choosing sustainable technologies such as electric vehicles. In such cases, adoption is not driven solely by individual benefit, but by the perception of a moral obligation toward society or future generations.

3.6.1. LIMITATIONS OF THE NAM

Despite its ethical significance, **NAM** presents several limitations from an operational standpoint.

First, it is a **highly subjective model**, based on variables that are difficult to measure objectively, such as personal moral norms or sense of responsibility. This can affect the replicability of empirical studies and the comparability across cultural contexts.

Second, the model does not incorporate **social or contextual dimensions**, such as peer group influence or the presence of external incentives, factors that can be decisive in purchasing decisions.

Finally, NAM assumes a **strongly normative view of human behaviour**, in which the individual always acts in alignment with their moral principles. In reality, behaviour is often more complex and may also be influenced by **convenience**, **habits**, or **conflicting emotions**.

3.7. INNOVATIONS DIFFUSION MODEL (ROGERS)

The **Diffusion of Innovations Model**, proposed by Everett Rogers in 1962 and later refined in subsequent editions of his seminal work, is one of the most well-known approaches for analysing how and why new technologies, products, or ideas are adopted over time by a population. Unlike models that focus on individual behaviour, Rogers' framework adopts a sociological and communicative perspective, examining the process through which an innovation spreads within a social system.

The model identifies five characteristics of an innovation that influence its rate of adoption:

- **Relative Advantage**: the degree to which the innovation is perceived as better than the existing alternative. In the case of electric vehicles (EVs), this may involve lower costs, access to restricted traffic zones, or quieter driving.
- **Compatibility**: the extent to which the innovation aligns with users' values, experiences and needs. For instance, EVs are more easily accepted by individuals with an established environmental consciousness.
- **Complexity**: the perceived difficulty in learning and using the innovation. If an EV is seen as complicated to charge or operate, adoption may slow down.
- **Trialability**: the possibility of trying out the innovation before making a commitment. Test drives, short-term rentals, or electric car-sharing services can help facilitate adoption.
- **Observability**: the extent to which the benefits of the innovation are visible to others. An EV may serve as a recognizable symbol of technological status or environmental commitment.

Another essential component of the model is the **categorization of adopters** into five groups, based on their openness to innovation and the timing of their adoption:

1. **Innovators (2,5%)**: the most open to change, with a high-risk appetite, strong technological curiosity and above-average financial resources. They are the first to try new products, even if they are expensive or not yet fully developed.

2. **Early Adopters (13,5%)**: a key segment in the diffusion process. While more cautious than innovators, they are opinion leaders within their social groups and significantly influence others' decisions. Their adoption often legitimizes the technology in the eyes of the broader public.
3. **Early Majority (34%)**: more reflective and cautious, they adopt the innovation only once it has proven useful and gained traction. They are pragmatic, seeking a good balance between benefit, reliability and risk.
4. **Late Majority (34%)**: sceptical and conservative, they adopt mainly for reasons of social conformity or because the innovation has become a standard. They often require external incentives (e.g., financial subsidies, regulatory mandates) to overcome their resistance.
5. **Laggards (16%)**: the last to adopt, typically when the innovation has already become mainstream. They tend to have limited access to resources, low trust in technology and prefer traditional solutions.

The distribution of these groups over time follows a **bell-shaped curve (normal distribution)**, while the cumulative adoption rate forms an **S-shaped curve** [Figure 8]. A key turning point in the diffusion process is reaching **critical mass**, which typically occurs between the early and late majority phases. Once this threshold is surpassed, the process becomes self-sustaining due to imitation effects, lower entry barriers and increased visibility of the innovation's benefits.

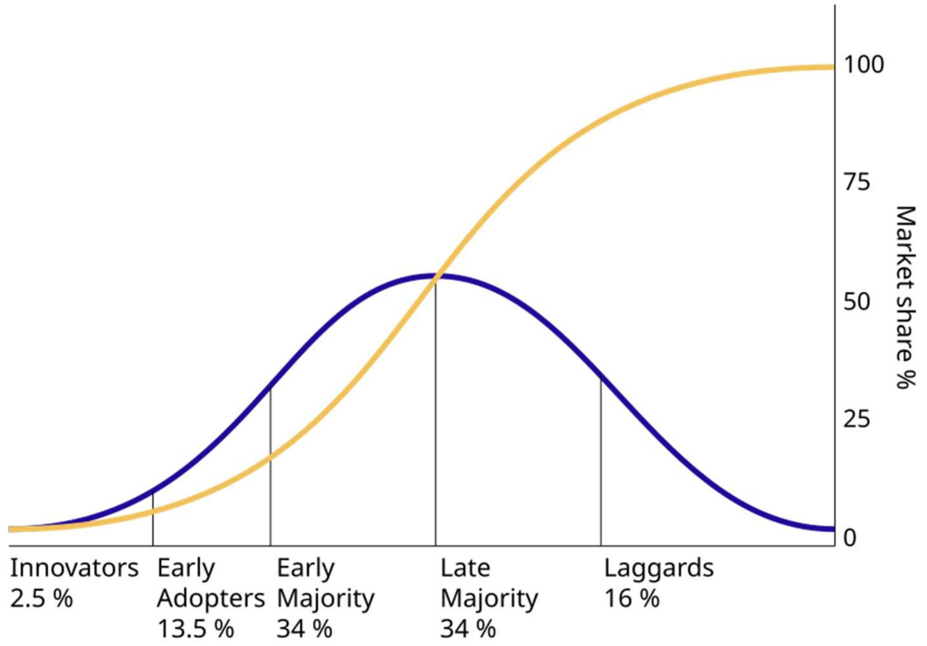

Figure 8: Cumulative and Adoption Curve of Innovation according to Rogers. Source: Diffusion of innovation – Wikipedia.

Rogers' model has been successfully applied in agriculture, public health, education, technology and marketing and is particularly useful for studying the diffusion of technological and sustainable products. In the automotive sector, it helps explain the speed or slowness with which electric vehicles are adopted and how to support the transition from niche to mainstream. It also serves as an effective tool for developing targeted communication strategies, user segmentation and incentive planning.

3.7.1. LIMITATIONS OF ROGERS' MODEL

Despite its broad applicability, **Rogers' model** has several theoretical weaknesses.

First, it is **primarily descriptive**: it explains how diffusion occurs, but not the underlying motivations that drive adoption at the individual level. Additionally, it assumes a **linear and progressive trajectory**, overlooking possible phenomena such as rejection, reversal, or disruption along the adoption curve.

Finally, the model tends to **underestimate the influence of cultural, regulatory and infrastructural contexts**, which can play a decisive role in the diffusion of complex innovations such as electric vehicles.

3.8. CONSUMER THEORY AND CUSTOMER EXPERIENCE

Consumer theory is one of the foundational pillars of microeconomics and aims to explain how individuals make decisions regarding the purchase of goods and services. In its classical formulation, the consumer is described as a **rational agent**, endowed with coherent and stable preferences, capable of **maximizing utility** within the limits of a given budget. This approach assumes that choices are based solely on objective evaluations, such as price, quantity and product quality (Samuelson, 1938).

However, over time, it has become clear that this model has important descriptive limitations, particularly in **high-emotional or symbolic consumption contexts**, such as the automotive sector. Interdisciplinary research has progressively expanded the economic perspective, integrating contributions from psychology, sociology and marketing. This has led to a more nuanced view of the consumer, not only as a utility maximiser but as a meaning-maker, emotion experiencer and participant in experiences.

In the behavioural paradigm, introduced by scholars such as Kahneman and Tversky (1979), consumer decisions are not always optimal but are subject to cognitive biases, heuristics and contextual influences. Consumers evaluate options based on subjective perceptions, past memories, social norms and future expectations. This shift has paved the way for a relational and dynamic understanding of consumption, in which the value attributed to a good or service is not intrinsic but rather constructed through individual experience.

Value itself is no longer seen as objective, but as **perceived value** (Zeithaml, 1988), resulting from the comparison between expected benefits and perceived costs. In this logic, elements such as **brand trust**, **quality of interaction** and **symbolic identification** with the consumed product become central. Particularly for complex goods like automobiles, functional dimensions intertwine with emotional and symbolic factors, turning the purchase act into a manifestation of personal and social identity.

In response to these changes, marketing has gradually shifted its focus from **customer satisfaction** to **customer experience**, understood as the set of perceptions and reactions generated throughout the entire interaction process with a brand, product, or service. According to Klaus and Maklan (2013), customer experience includes cognitive, affective, sensory and behavioural components and it develops at every **touchpoint** between consumer and company, from information search to post-purchase usage. It is therefore a complex and dynamic process, evolving through all stages of the so-called **customer journey**, from first contact to post-purchase engagement.

The **experiential approach** was formally introduced by Holbrook and Hirschman (1982), who challenged the purely utilitarian view of consumption and emphasized the role of fantasy, emotions and symbolism in the creation of value. Since then, customer experience has established itself as an independent field of study, with applications across a wide range of sectors, including automotive, where purchasing decisions are not purely rational but charged with expectations, status and desire.

According to the model proposed by Solis (2019), **customer experience** can be broken down into four core dimensions:

- **Functional**: related to the quality, reliability and efficiency of the product.
- **Emotional**: connected to the emotions experienced during interaction with the brand.
- **Relational**: referring to the quality of interpersonal or digital interactions.
- **Symbolic**: associated with meanings attributed to the product, such as sustainability, status, or lifestyle.

These dimensions are essential for generating **satisfaction**, which is a key outcome of customer experience. Satisfaction arises when **explicit or implicit expectations** are met or exceeded throughout the interaction with the product or company. A positive customer experience not only increases satisfaction, but also strengthens loyalty, that is, the customer's propensity to repurchase or recommend the product.

Today, companies monitor these dynamics using quantitative tools such as:

- **Net Promoter Score (NPS)**: measures the likelihood of a customer recommending the brand.
- **Customer Satisfaction Score (CSAT)**: assesses satisfaction at specific touchpoints.
- **Customer Lifetime Value (CLV)**: evaluates the economic value a customer generates over time.

In its most recent evolution, consumer theory adopts a multidimensional perspective, integrating rationality, emotions, relationships and values. Within this framework, customer experience serves as a theoretical and operational bridge between economic models and business practices, offering an interpretive lens for understanding purchasing behaviour in complex contexts.

In the case of the automotive sector, where the adoption of new technologies involves cultural, infrastructural and psychological changes, customer experience becomes even more relevant. Chapter 4 of this thesis will apply these concepts to analyse consumer behaviour in the car market, with a particular focus on the transition from internal combustion vehicles to hybrid and electric solutions.

3.8.1. THE CUSTOMER JOURNEY MAP AS A TOOL FOR UNDERSTANDING AND OPTIMIZING BEHAVIOUR

In the context of customer experience management, one of the most effective analytical tools for understanding and optimizing consumer behaviour is the **customer journey map**. This is a **visual and sequential representation** that describes all the stages a customer goes through during their interaction with a product or service, from brand discovery to the post-purchase relationship.

Each stage includes specific **touchpoints**, that is, moments of contact between the customer and the company that can **positively or negatively influence** overall perception. Journey map analysis helps identify:

- **Pain points**: critical moments that generate friction, frustration, or disengagement.
- **Moments of truth**: decisive interactions that shape the overall evaluation of the brand.
- **Opportunities for innovation**: areas where processes, tools, or communication can be improved to increase engagement.

The purpose of this tool is not only **descriptive** but also **strategic**: it enables the identification of key moments along the journey, the analysis of potential issues and the design of more coherent and personalized experiences.

According to scholars such as Prim (2015) and Richardson (2010), the customer journey map plays a crucial role in aligning experiences across various channels and touchpoints, thereby transforming the customer relationship into a co-created and dynamic process.

4. THE APPLICATION OF ACCEPTANCE MODELS AND CUSTOMER EXPERIENCE TO THE AUTOMOTIVE SECTOR

Technological change and growing attention to environmental sustainability are profoundly transforming the automotive sector. In this context, **consumer behaviour** plays a central role in determining the success of newly introduced innovations, particularly with regard to the adoption of electric vehicles, hybrid powertrains and new integrated digital solutions. The mere availability and performance of a technology are not sufficient: its diffusion largely depends on user perceptions, expectations and experiences.

Based on the theoretical framework outlined in Chapter 3, which presented the main technology acceptance models and the evolution of consumer theory toward an experiential and relational perspective, this chapter aims to apply these theoretical references to the specific context of the automotive sector. The goal is to analyse in a structured way the factors influencing purchasing behaviour and the adoption of technological solutions in today's car market.

The chapter explores the application of acceptance models in the automotive domain, with particular attention to their explanatory power regarding the intention to adopt new powertrains and technologies. It also examines the role of customer experience as a key component of consumer behaviour, analysing the perceived quality of brand interactions, the impact of emotions and symbolic values and the growing importance of user experience as a competitive lever. The chapter then analyses the customer journey map as a tool for understanding decision-making processes, highlighting critical touchpoints, expectations and barriers to adoption.

Finally, it focuses on the evolution of consumer preferences between internal combustion, hybrid and electric vehicles, the effects of technological innovation and public policies on consumer choices and the main psychological, social and economic factors shaping purchasing behaviour.

4.1. ACCEPTANCE MODELS IN THE AUTOMOTIVE SECTOR

Technology acceptance models serve as a key theoretical framework for analysing how consumers adopt new technologies and they have been widely applied in the automotive sector, particularly to understand the intention to purchase electric (EV) and hybrid vehicles. The main constructs of models, already discussed in Chapter 3, have proven effective in predicting attitudes and behaviours toward the adoption of sustainable mobility solutions.

Numerous empirical studies conducted across different countries highlight the predictive validity of variables such as Perceived Usefulness, Ease of Use, Social Influence and Facilitating Conditions.

In a study by Jain et al. (2021) conducted in India, an integrated UTAUT model was developed that included additional variables such as Environmental Concern, Government Support and Perceived Risk. The results showed that Social Influence, Perceived Ease of Use and Facilitating Conditions significantly impact the intention to adopt electric vehicles, while the others act as a psychological barrier to purchase.

The study by Ong et al. (2023) integrated the Sustainability Theory of Planned Behaviour (STPB) with UTAUT2 to examine the factors influencing the intention to purchase hybrid vehicles in the Philippines. The results showed that traditional TPB constructs (Attitude, Subjective Norm and Perceived Behavioural Control) played a key role, particularly when influenced by sustainability concerns, including environmental awareness, financial aspects, and institutional support. Within the UTAUT2 model, constructs like Performance Expectancy, Hedonic Motivation and Price Value emerged as significant, whereas others such as Effort Expectancy, Habit and Facilitating Conditions showed no substantial effect.

Another relevant contribution is provided by Durmuş Şenyapar et al. (2023), who conducted a bibliometric analysis of the literature on electric vehicle consumer behaviour in Turkey between 2004 and 2022. Using methods such as co-citation, keyword co-occurrence and thematic mapping, the study identified key research trends and highlighted the growing academic interest in environmental awareness, economic incentives and public policy as key influences on EV adoption.

From a cultural perspective, Zhang et al. (2022) apply the Value-Belief-Norm (VBN) Theory to explore how cultural factors, particularly collectivism, influence the link between environmental values and electric vehicle adoption intentions in China. Their findings suggest that VBN is a useful framework for understanding pro-environmental behaviour and that collectivist orientations amplify the role of personal moral obligations in shaping these intentions.

Finally, a systematic literature review by Rezvani et al. (2015), updated in recent studies, suggests that in addition to instrumental constructs, hedonic and symbolic factors should also be considered, such as perceptions of modernity, driving pleasure and personal identity associated with EV usage. This has led to growing interest in hybrid and dynamic models that integrate rational and emotional dimensions.

In the **Italian context**, although the literature remains limited, there is growing attention to the interaction between social variables, available infrastructure and perceived economic benefits. Expected Performance (e.g., range, operating costs, tax benefits) and Facilitating Conditions (e.g., access to charging stations, availability of regional incentives) are among the most important criteria influencing consumer choices.

4.1.1. LIMITATIONS AND ADAPTABILITY OF THE MODELS

Although TAM and UTAUT represent solid and widely validated theoretical tools for analysing technology acceptance, they present several practical limitations, particularly when applied outside of organizational contexts and into individual consumer settings.

First, these models were originally developed to study technology adoption in **professional or organizational environments**, where system usage is often mandatory, or productivity driven. As such, they tend to focus on the functional and rational aspects of behaviour. In contrast, in the automotive market, purchasing decisions are voluntary and strongly influenced by **emotional**, **identity-related** and **symbolic factors**. Consumers choose a vehicle not only for its perceived utility, but also for what it represents in terms of **status**, **lifestyle**, or **personal values**. These affective, cultural and narrative dimensions are often overlooked in the classic versions of acceptance models, which do not fully account for the role of hedonic perception, social image, or brand identity in shaping behavioural intentions.

To address these shortcomings, recent literature has begun to integrate traditional models with more complex and multidimensional approaches, such as the **Value-Belief-Norm (VBN) Theory**, which considers the influence of personal values and internalized moral norms, or frameworks based on customer experience, which incorporate emotional, relational and symbolic factors. These integrations help to better capture the deep motivations driving the adoption of sustainable technologies such as electric vehicles, where rationality is only one part of the decision-making process.

Despite these limitations, acceptance models still provide significant analytical value, especially due to their ability to structure and measure variables such as Perceived Usefulness (Performance Expectancy), Ease of Use (Effort Expectancy), Social Influence, Trust in

Technology, Environmental Conditions and Economic Value. When properly adapted and enriched, these models remain excellent tools for understanding how consumers evaluate and adopt new solutions in the mobility sector.

4.2. CUSTOMER EXPERIENCE IN THE AUTOMOTIVE SECTOR

In recent years, the concept of **customer experience** has assumed a central role in marketing strategies and in the management of relationships between companies and customers. In the automotive sector, customer experience represents a **strategic element**. The purchase of a car is a process marked by high emotional, economic and symbolic involvement, in which the customer evaluates not only the technical features of the vehicle but the entire system of experiences: information search, dealership visit, interaction with the online configurator, commercial negotiation, personalized delivery and after-sales support. Each touchpoint, whether physical or digital, contributes to forming the customer's overall perception of the brand.

Customer experience is **multidimensional**, involving both **tangible elements** (product quality, service efficiency) and **intangible ones** (emotions, perceived consistency, relationship). Specifically, four dimensions are particularly relevant in the automotive industry:

- **Functional**: relates to the perceived quality of the vehicle, its performance, reliability and technological innovation. For example, the car must meet expectations in terms of fuel consumption, comfort, safety and technological features.
- **Emotional**: includes the feelings elicited by the brand, the sense of belonging, trust and excitement generated by the interaction. Vehicle aesthetics, the way it is presented at the dealership, or staff courtesy all contribute to a positive emotional response.
- **Relational**: refers to the quality of interactions with staff, communication transparency and the attention received during and after the purchase. In the automotive context, this includes interaction with salespeople, the efficiency of after-sales service and the company's responsiveness to requests or complaints.
- **Symbolic**: concerns the identity and values the customer associates with the brand. For many consumers, the car is an extension of the self: it reflects status, lifestyle and value alignment (e.g., sustainability).

These components are perceived differently by different customer segments. For example, younger consumers (Generations Y and Z) place strong emphasis on digitalization, product sustainability and personalization of service. In contrast, older clients tend to value brand reliability, safety and in-person dealership service.

In the automotive market, characterized by **long purchase cycles** and **high unit values**, customer retention is a strategic asset. A satisfied customer is more likely to repurchase from the same brand or subscribe to related services (leasing, maintenance, insurance). Trust and perceived consistency over time strengthen the relationship between customer and company, creating a sustainable competitive advantage.

Recent studies confirm that customer experience in the automotive sector directly impacts not only customer satisfaction, but also **purchase intention**, **brand loyalty** and **positive word-of-mouth**. In particular, the consistency across the various physical and digital touchpoints along the customer journey has emerged as a critical factor. If not properly managed, fragmentation of the experience across channels can create perceptual discontinuities and damage consumer trust.

In a market increasingly focused on experience, the ability of car manufacturers to design memorable and meaningful interactions becomes a distinctive advantage. This implies not only the adoption of analytical tools such as the customer journey map, but also the development of an organizational culture centred on listening, personalization and customer centrality.

In the context of sustainable mobility, experience also takes on a value-based dimension: the adoption of an electric vehicle, for example, does not only respond to considerations of savings or performance, but can also represent an ethical choice, a personal commitment to the environment, or a desire to align with more responsible lifestyles. All of this reinforces the idea that customer experience in the automotive sector should not be viewed as an extension of the product, but as an integral part of the value proposition.

4.2.1. THE CUSTOMER JOURNEY MAP

The **customer journey map** is one of the most effective tools for analysing and designing the customer experience across all stages of interaction with a brand or product. Unlike static analytical approaches, the customer journey map enables a **dynamic, multidimensional and contextualized visualization** of consumer behaviour, linking **goals**, **emotions**, **barriers** and **opportunities** at each stage of the relationship.

In the automotive sector, the customer journey map proves especially useful, as it allows companies to chart a long, complex and high-involvement purchasing process, which includes both rational and emotional components, as well as functional and symbolic aspects. The experience extends well beyond the purchase itself, beginning with the exploration phase and potentially continuing for years through daily vehicle use, maintenance, after-sales interactions and, in some cases, vehicle resale.

The journey map typically unfolds across several sequential phases, each associated with specific **touchpoints** and a corresponding **customer experience**. In the automotive context, the journey can be divided as follows:

- **Awareness**: the potential customer becomes aware of the brand or product through advertising campaigns, social media, promotional test drives, or events. The goal at this stage is to generate interest and spark curiosity.
- **Consideration**: the customer deepens their knowledge, compares models and trims, reads reviews and visits official websites or comparison platforms. This stage is dominated by rational evaluation and alternative analysis.
- **Test/Experience**: this is the first physical contact with the product. The customer visits the dealership, test drives the vehicle, evaluates financing options, interacts with sales staff and forms a concrete impression of the brand.
- **Decision/Purchase**: the customer selects a model, defines payment terms and completes the purchase. This experience can be enhanced with symbolic and emotional elements (e.g., personalized delivery, welcome messages, gifts).
- **Ownership**: the customer uses the vehicle on a daily basis, interacts with after-sales services, accesses technical support and evaluates the experience over time. It is at this stage that the relationship with the brand is either solidified or weakened.

Beyond merely describing the journey, the customer journey map helps identify moments of truth, interactions that decisively shape the customer's opinion and pain points, i.e., critical areas where the experience may result in frustration, confusion, or inconsistency. The objective of this analysis is to optimize the journey, making it seamless, coherent and memorable through careful design of both touchpoints and content.

Using the customer journey map in the automotive context offers several practical **advantages**. First, it enables the **segmentation of customer paths** based on relevant variables such as customer type (e.g., private or corporate), vehicle type (new or used, electric or combustion) and preferred sales channel (physical or digital). This level of detail allows companies to tailor strategies to the specific needs of different targets.

Second, mapping the customer journey allows for a more precise **identification of unmet expectations**, which can lead to dissatisfaction or even churn. Another important aspect is the ability to evaluate the balance between digital and physical channels, a crucial factor in ensuring coherent and fluid hybrid experiences.

Finally, this tool is particularly valuable for designing **personalized content and services**, tailored to the needs that emerge at different stages of the consumer's decision-making and purchasing process.

An effective customer journey map is not a static tool, but a model that must be continuously updated through qualitative and quantitative analysis. Interviews, field observations, structured surveys and key performance indicators (e.g., Net Promoter Score, Customer Satisfaction Score, Customer Lifetime Value) allow the map to be adapted to evolving consumer behaviour, technologies and expectations.

In the case of electric vehicles, for example, a well-constructed journey map can highlight critical issues in the post-purchase phase, such as range anxiety, difficulty finding charging stations, or lack of technical support. The company can then take targeted action, improving the customer experience and reinforcing trust in the product [Figure 9].

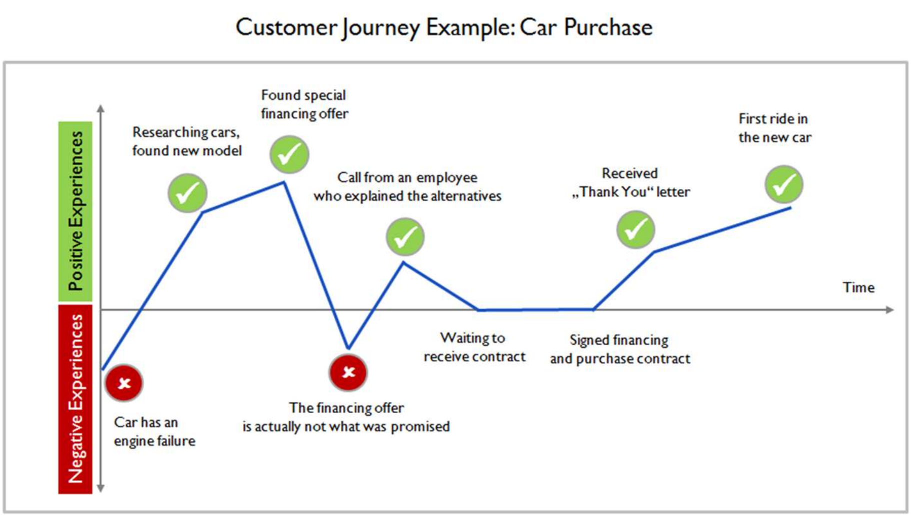

Figure 9: Example of a customer journey in car purchasing. Source: Customer journey mapping - Gravity Flow.

4.3. CONSUMER PREFERENCES BETWEEN INTERNAL COMBUSTION, HYBRID AND ELECTRIC VEHICLES

In recent years, the automotive market offering has become increasingly diverse. Alongside internal combustion engine (ICE) vehicles, there are now hybrid models (both HEV and PHEV) and fully electric vehicles (EVs), each with specific advantages and limitations [Table 1]. Hybrids often serve as an entry point to electrified mobility, while EVs promise zero local emissions, but require infrastructure development and more significant behavioural changes.

This transformation, driven by stricter environmental regulations, economic incentives and rising ecological awareness, is far from linear. Consumer preferences vary widely depending on individual, socioeconomic, cultural and infrastructural factors, creating a complex landscape that requires thorough analysis.

Several studies have attempted to identify the factors influencing the choice among ICE, HEV and EV. The literature suggests these can be grouped into five macro-categories:

- **Economic aspects**: purchase price, maintenance costs, tax benefits and fuel savings play a central role. In a study conducted in Poland, Sobiech-Grabka et al. (2022) highlight that while purchase price remains the main barrier to EV adoption, environmental concern plays a minor role even among younger and more educated consumers.
- **Infrastructure and ease of use**: vehicle range, availability of charging stations and charging times significantly influence the decision. As shown by Burke et al. (2020) in the Californian context, EV adoption is higher in areas with developed infrastructure and tangible logistical benefits (e.g., access to carpool lanes or reserved parking).
- **Environmental and value-driven factors**: awareness of the positive environmental impacts of EVs plays a key role. Studies from India and Greece (Vijai Krishnan & Koshy, 2021; Shaban et al., 2022) emphasize that environmental concern and personal responsibility are significant predictors of purchase intention.
- **Perceived technology and innovation**: interest in advanced technologies, the quiet driving experience, digital connectivity and driving comfort influence choices, especially among tech-savvy consumers. In a study, Nigam et al. (2024) highlight the importance of perceived usefulness, technological perception and individual attitudes as key determinants of adoption.

- **Identity, symbolism and lifestyle**: electric and hybrid vehicles are often perceived as symbolic goods, capable of expressing values such as modernity, sustainability and membership in innovation-oriented communities (Rezvani et al., 2015). In this sense, a car is not just a means of transport but a vehicle of identity.

In emerging markets, such as Brazil and India, preferences still appear strongly influenced by economic and infrastructural variables. However, growing environmental awareness is evident. In a systematic review on Brazil, Schvartz et al. (2024) identify economic factors, infrastructure availability, and consumer perceptions as the most influential variables shaping electric vehicle purchase decisions.

In mature markets, such as California and several European countries, the transition toward EVs is more pronounced, supported by structured incentives, widespread infrastructure and stringent regulations. Nonetheless, even in these contexts, EV adoption is still closely linked to risk perception and the level of technological familiarity.

An additional contribution comes from Ong et al. (2023), who use an AI-based predictive model to demonstrate that a combination of sociodemographic factors, environmental motivations and technological availability can accurately predict hybrid vehicle purchase intentions.

Table 1: Comparison between internal combustion engine (ICE), hybrid (HEV/PHEV) and electric vehicles (EV). Source: Author's elaboration.

Characteristics	ICE (internal combustion)	HEV/PHEV (hybrids)	EV (electric)
Average purchase price (€)	18.000 - 25.000	22.000 - 35.000	28.000 - 45.000
Annual running costs (€)	1.500 - 2.200	1.200 - 1.800	500 - 800
Average driving range (km)	800 - 1.000	600 - 900 (EV only: 40-60 km)	300 - 500
Refuelling/recharging cost (€)	80 - 100 (gasoline)	40 - 60 (fuel/electricity)	20 - 30 (electricity)
CO_2 emissions (g/km)	110 - 130	60 - 90	0 (direct use)

Access to restricted zones/free parking	Limited or absent	Partial (city-dependent)	Often available
Public incentives (€)	0 - 2.000	1.500 - 3.000	3.000 - 7.500
Social perception	Traditional, practical	Ecological, moderately innovative	Innovative, sustainable

4.4. TECHNOLOGICAL EVOLUTION AND IMPLICATIONS FOR PURCHASING BEHAVIOUR

In recent years, purchasing behaviour in the automotive sector has been deeply influenced by technological evolution, which has reshaped not only vehicle features but also the way consumers evaluate, choose and experience the buying process. The growing presence of electric, hybrid and connected vehicles intersects with innovations in business models, distribution channels and the design of the customer journey. These transformations require a new approach to understanding consumer decision-making dynamics.

The **internet** has revolutionized access to information: consumers can now compare dozens of models, read reviews and calculate costs and benefits, all within minutes. This has made them more informed but also more demanding.

The introduction of new propulsion technologies and advanced driver assistance systems (ADAS) has reshaped buyers' expectations. The increasing availability of low- or zero-emission vehicles, the electrification of product lines and the integration with digital platforms (e.g., vehicle management apps, personalized infotainment systems) have expanded the range of decision-making criteria, shifting the focus from purely mechanical attributes to values such as sustainability, connectivity and energy efficiency.

In this sense, the **technological transition** goes beyond replacing combustion engines with electric motors, it involves the entire product-service system. As highlighted by Choi & Koo (2023), the introduction of new technologies into the market requires strategies that consider consumer psychological profiles, the presence of established competitors and regulatory interventions.

Consumer choices are also strongly influenced by **sustainable mobility policies**, such as purchase incentives, tax exemptions and privileged access to urban areas. At the European level, the Green Deal and the "Fit for 55" package aim to phase out the sale of combustion vehicles by 2035, accompanied by incentives for electrification, infrastructure investments and increasingly strict CO_2 emission regulations. Studies such as Wang & Li (2021) show that demand-side subsidies (e.g., purchase discounts) have a more direct and immediate impact than supply-side regulations, although both must be balanced to effectively stimulate the market.

In the European context, particularly in Poland, Sendek-Matysiak and Łosiewicz (2021) highlight that the growth of the electromobility market is closely linked to the consistency and visibility of public policies. Incentives that are unstable or perceived as temporary can generate distrust and delay adoption.

The effect of **combined policy instruments** has also been studied by Wang et al. (2023), who analyse the interaction between price competition and joint investments in low-energy-consumption technologies. Their model shows that under frameworks like China's "double-points policy," firms are encouraged to innovate, but only if supported by a stable regulatory environment and an informed, engaged demand base.

Alongside technological and regulatory changes, the purchasing experience has also evolved significantly. The **customer journey** has shifted from a predominantly linear process to a **dynamic, fragmented** and **omnichannel experience**. Today, consumers interact with automotive brands through a wide range of physical and digital touchpoints, often in a non-sequential manner. All these touchpoints contribute, in an integrated way, to the overall customer experience.

This new configuration of the purchasing path requires car manufacturers to ensure consistency in language, functionality and design across websites, mobile apps, physical dealerships, email marketing campaigns, post-sales CRM systems and social media.

In addition to functional aspects, the **emotional dimension** plays an increasingly decisive role: purchasing decisions, especially in high-involvement sectors like automotive, are not based solely on rational evaluations, but are strongly influenced by the emotions elicited during brand interactions. As emphasized by Prim (2015) and Solis (2019), designing a coherent and engaging experience means going beyond functionality to create memorable moments that evoke positive emotions, a sense of belonging and perceived value.

For this reason, innovative brands invest in **experience innovation**, creating emotionally resonant moments (e.g., personalized welcome kits at delivery, custom apps, empathetic customer service) that transform a simple purchase into a meaningful experience. The goal is not just to sell a product, but to guide the customer through a coherent, engaging and personalized journey, capable of generating mutual value.

In this context, technological evolution cannot be analysed in isolation: it generates profound impacts on purchase motivations, influencing not only what is bought, but also how and why it is bought.

4.4.1. THE ITALIAN CASE: CONSUMER BEHAVIOUR, PERCEPTIONS AND BARRIERS

In the **Italian context**, consumer behaviour in the automotive sector exhibits certain specific characteristics that warrant attention. Italy has historically been a market strongly tied to internal combustion vehicles, with a high share of gasoline and diesel cars compared to other European countries. Nevertheless, in recent years, interest in hybrid and electric solutions has increased, driven by information campaigns, environmental regulations and the introduction of national and local incentives.

Despite this trend, the adoption of electric vehicles remains limited in comparison to countries such as Norway, Germany, or the Netherlands. Italian consumers tend to be cautious and sensitive to factors such as purchase price, availability of charging infrastructure and actual knowledge of the technology. According to data from the Italian Ministry of Infrastructure and Transport, in 2023 fully electric vehicles accounted for less than 5% of total registrations, whereas hybrid vehicles experienced more consistent growth.

These figures suggest that a successful energy transition in the Italian automotive sector must address the specific needs and concerns of local consumers. Factors such as the coverage of charging infrastructure, the geographic gap between north and south and differences between urban and rural areas lead to uneven levels of technological adoption. In addition, doubts persist regarding battery life and the residual value of electric vehicles in the used car market.

Another important aspect to consider is the relationship between Italian consumers and car **brands**. The brand, often associated with tradition, prestige and reliability, plays a significant role in consumer decisions. It is no coincidence that Italian brands such as Fiat or Alfa Romeo continue to hold a substantial market share, even in a globalized landscape. However, the growing interest in innovative brands like Tesla, along with the increasing presence of competitive Asian manufacturers, indicates that brand loyalty is evolving, particularly among younger consumers.

4.5. PSYCHOLOGICAL, SOCIAL, ECONOMIC AND ENVIRONMENTAL FACTORS IN THE ADOPTION OF NEW TECHNOLOGIES

In the past, **price**, **fuel consumption** and **vehicle performance** were likely the dominant criteria in purchasing decisions. Today, while these aspects remain central, they are no longer sufficient on their own to explain consumer behaviour. Choices are increasingly shaped by **subjective, value-driven and symbolic evaluations** [Figure 10].

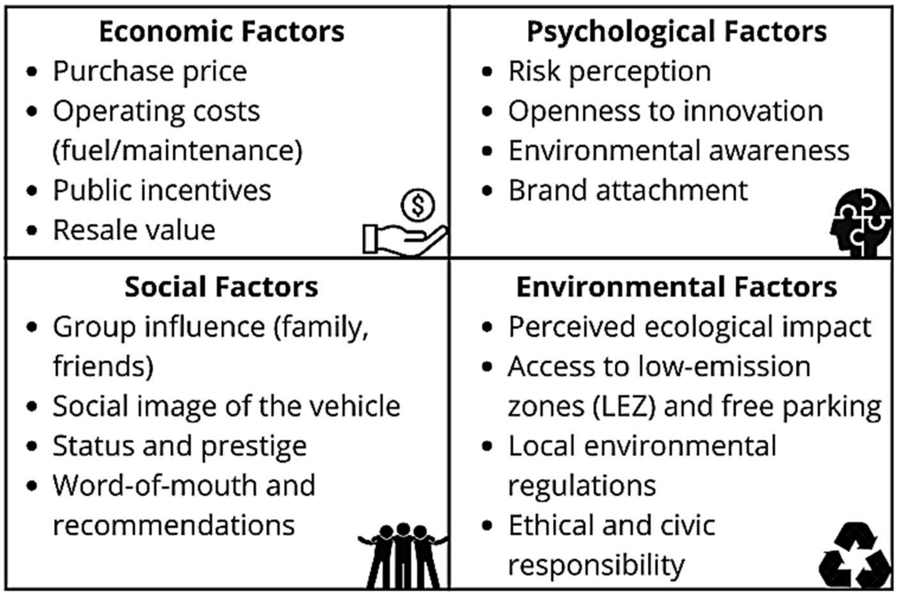

Figure 10: Factors influencing the decision to purchase a car. Source: Author's elaboration.

Economic factors, such as purchase price, long-term operating costs and the availability of purchase incentives, continue to play a key role, especially in contexts where purchasing power is limited, or upfront EV costs remain high. In many Eastern European countries, purchase price and the availability of public incentives are still the main drivers or barriers to EV adoption.

At the same time, adequate and accessible charging infrastructure is considered a crucial enabling condition. A lack of widespread networks, particularly in rural areas, hinders EV diffusion, whereas tax incentives, access to low-emission zones and parking benefits contribute to making them more attractive.

From a **psychological perspective**, many studies highlight how attitudes toward innovation, risk tolerance and environmental awareness significantly influence adoption intentions. Ju & Kim (2022) show that psychological resistance to EVs is stronger among consumers who fear issues related to range, battery life, or maintenance. However, the same study also indicates that environmentally conscious millennials are more willing to accept these limitations in favor of sustainable change.

Consumer decisions are also strongly shaped by **social norms**, **shared experiences** and **brand trust**. The recommendations from friends and family, brand reputation and social media visibility influence product credibility. In this sense, choosing a car becomes a relational and communicative act, where the vehicle's image reflects the buyer's lifestyle.

According to Klaus & Maklan (2013), customer experience, understood as the sum of perceptions generated at every brand touchpoint, plays a decisive role in shaping trust, satisfaction and loyalty. Elements such as comfort, design, after-sales support and information transparency strongly affect purchase likelihood, often beyond technical specifications.

Recent research also suggests that **ethical**, **symbolic** and **hedonic dimensions** increasingly influence buying motivations. Studies on instrumental, symbolic and hedonic attributes demonstrate that many consumers choose EVs not only for practical benefits, but also to express personal values, such as environmental concern or alignment with a modern and responsible lifestyle.

These factors are particularly significant among younger generations, who tend to see EV adoption as a form of collective action and social participation, contributing to emissions reduction and the promotion of more sustainable development. In this view, the car becomes an extension of consumer identity.

Finally, a crucial factor is the growing **environmental consciousness** among consumers. Awareness campaigns, EU regulations and the increasing availability of information on urban traffic impact are shifting public perception. Especially among the younger population, there is a strong desire to contribute to emissions reduction and actively support the transition to sustainable mobility. Today, purchasing an electric vehicle is not only a functional decision, but also a way to feel part of a positive change. Many consumers attribute ethical value to their purchase, especially in urban contexts where traffic restrictions and low-emission zones incentivize the use of less polluting vehicles.

5. CONSTRUCTION OF THE ANALYTICAL MODEL

After outlining, in the previous chapters, the main theoretical models of technology acceptance and exploring their applications to the automotive sector, this chapter focuses on the construction of an original analytical model, designed to investigate the factors that influence the intention and usage behaviour of Italian consumers towards electric and hybrid vehicles. The objective is to propose a theoretical framework that is concise yet comprehensive, integrating cognitive, social, value-based and experiential dimensions that are relevant in the transition towards more sustainable forms of mobility.

The chapter is divided into five subsections: the first (5.1) presents the theoretical proposal of the model, the second (5.2) examines its variables, research hypotheses and interdependencies, the third (5.3) illustrates the design of the questionnaire as an empirical data collection tool, the fourth (5.4) describes the sampling criteria based on updated ISTAT data and the final subsection (5.5) introduces the methodological strategy for analysis and the segmentation of behavioural outcomes.

The overall objective of the chapter is to build a solid and coherent theoretical and methodological foundation, capable of supporting the data analysis presented in the following chapter and contributing in an original way to the understanding of the dynamics of technology adoption in the Italian automotive market.

5.1. THEORETICAL MODEL PROPOSAL

The evolution of consumer behaviour toward emerging technologies in the automotive sector calls for a reflection on how theory can be integrated with the specific features of this context. After analysing, in the previous chapters, the main interpretive models of technology acceptance, from TAM and its extensions, to UTAUT and UTAUT2 and including complementary approaches such as TPB, NAM and Customer Experience Theory, an analytical model is proposed to explain, in a way that is consistent with the literature and relevant to the Italian case, the factors influencing the intention and usage behaviour regarding electric and hybrid vehicles [Figure 11].

Unlike traditional models, often composed of multiple constructs and sub-variables, the model proposed in this research aims for a **functional synthesis** between theoretical rigor and operational simplicity. In this regard, the canonical variables from the literature are grouped and reinterpreted into four **macro theoretical dimensions**, each representing a key area in the consumer's experience and decision-making process related to sustainable mobility.

The first dimension, **Technology Appraisal**, encompasses the traditional constructs of Performance Expectancy and Effort Expectancy and measures the degree to which the individual perceives the technology as useful, accessible, reliable and aligned with their needs. This aggregation is inspired by both TAM and UTAUT2, but also incorporates elements of compatibility and technological trust, which are more central in recent consumer-focused models. In a market still subject to uncertainties regarding the actual performance of electric and hybrid vehicles, this dimension serves as a crucial indicator of adoption propensity.

The second dimension, **Socio-Environmental Influence**, combines the variables of Social Influence and Personal Norms. This component merges perceived social pressure, stemming from family, friends and cultural context, with value-based and normative motivations related to the environment. The aim is to capture not only the effect of others' opinions but also that of personal beliefs regarding the moral duty to act sustainably. This construct is conceptually derived from both TPB (Subjective Norms) and NAM (Personal Norms) and allows for a more comprehensive measurement of the social and ethical influences on technological choices.

The third dimension, **Consumer Experience Engagement**, results from the integration of Facilitating Conditions, Hedonic Motivation, Habit and Customer Experience. This variable considers how users interact with the entire technological ecosystem associated with electric or hybrid vehicles: from the ease of using digital services, to the quality of daily experience, the pleasure of use and the strength of habits. This synthesis reflects the centrality of the experiential component in contemporary marketing and is grounded in the literature on customer experience and in recent developments of UTAUT2, which include affective and behavioural continuity aspects. In the mobility context, where the relationship with technology is pervasive, multisensory and long-lasting, this dimension provides a fundamental interpretation of user engagement.

Finally, the fourth dimension, **Perceived Value**, measures the balance between perceived costs and benefits. It corresponds to one of the variables introduced in UTAUT2, but in this model it is emphasized for its relevance in the Italian context, where the price of electric vehicles remains one of the main barriers to purchase. The construct includes not only an economic evaluation, but also the subjective perception of convenience compared to using a combustion vehicle. Its centrality allows for an understanding of economic rationality in consumer decisions, in combination with symbolic, social and functional factors.

These four macro-variables directly influence **Behaviour Intention** (dependent variable), which in turn may translate into Actual Behaviours, such as the use or purchase of an electric or hybrid vehicle.

Unlike traditional models that predict a single behavioural intention, the present model distinguishes between **three different behavioural outcomes**: the use of electric vehicles (EV), the use of hybrid vehicles and the use of traditional internal combustion engine (ICE) vehicles. This segmentation allows for a more nuanced understanding of technological adoption dynamics, recognizing that motivations, barriers and perceptions may vary significantly depending on the technology considered.

The model also includes **six sociodemographic moderating variables**: age, gender, education level, household income, type of residence (urban, suburban, rural) and driving experience. These moderators will make it possible to explore how the relationships between the four independent variables and adoption intention vary according to the individual’s profile.

The model’s synthetic yet integrated structure allows it to overcome the limitations of more rigid frameworks, offering a flexible, up-to-date and context-specific tool for analysing sustainable mobility in Italy. Its validity will be tested empirically through a **structured questionnaire**, developed based on the constructs described above and administered to a representative sample of the national population. The goal is to build a solid bridge between theory and practice, in order to gain a deeper understanding of the mechanisms that drive the adoption of electric and hybrid vehicles in our social and economic context.

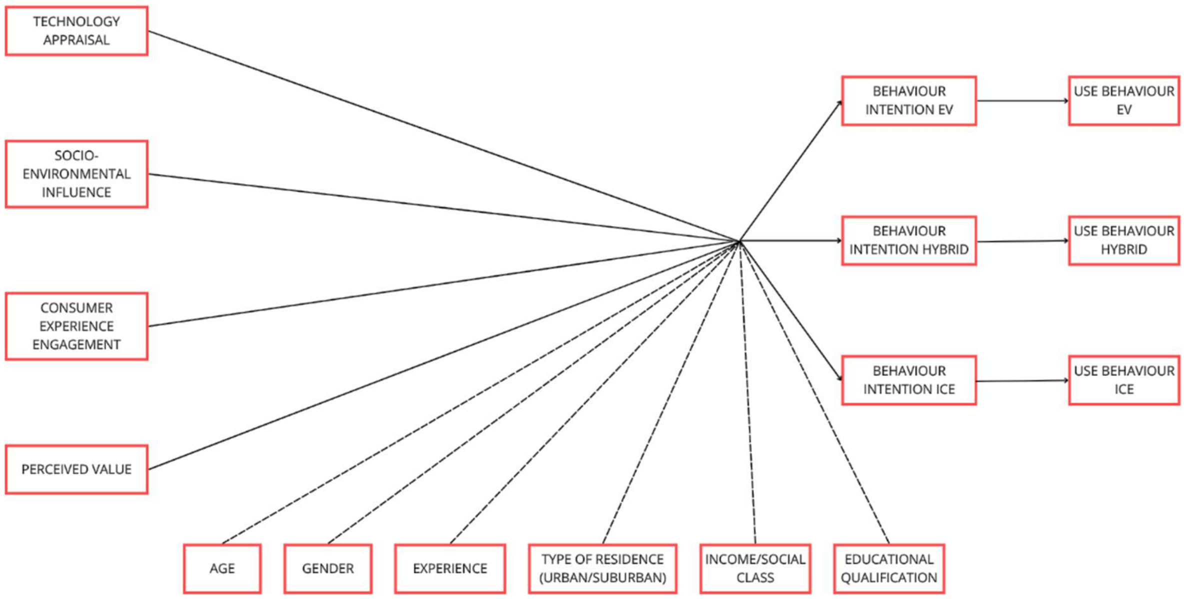

Figure 11: Conceptual model of consumer behaviour in the adoption of automotive technologies. Source: Author's elaboration.

5.2. DEFINITION OF VARIABLES AND RESEARCH HYPOTHESES

The conceptual model proposed in this study integrates the main theories of technology acceptance, consumer behaviour and customer experience, with the aim of understanding the factors that influence the adoption of electric, hybrid and internal combustion vehicles. The selected variables reflect the cognitive, emotional, social and value-based dimensions that guide choices related to sustainable mobility. The following section describes the operational variables of the model, along with the corresponding research hypotheses [Figure 12].

The first variable, **Technology Appraisal**, reflects individuals' cognitive and functional evaluations of the technology. It includes aspects such as Perceived Usefulness, Ease of Use, compatibility with one's needs and trust in the technological solution. The underlying assumption is that the more consumers perceive electric and hybrid vehicles as useful, easy to use and compatible with their needs and habits, the greater their intention to adopt them. This leads to the first research hypothesis: **the higher the Technology Appraisal, the higher the intention to purchase an electric or hybrid vehicle (H1)**.

The second variable, **Socio-Environmental Influence**, encompasses both Social Influence and personal orientation toward sustainability. In doing so, the variable captures both the pressure from the social environment (family, friends, colleagues) and the moral and value-based drive to adopt more sustainable behaviours. The corresponding hypothesis is **the higher the Socio-**

Environmental Influence, the higher the intention to purchase an electric or hybrid vehicle (H2).

The third variable, **Consumer Experience Engagement**, represents the individual's level of experiential involvement in the interaction with the product, associated services and the overall technological ecosystem. This construct includes both practical aspects (e.g., usability of apps and services) and emotional and relational elements linked to vehicle management. In a highly engaging context such as automotive, past experience and a seamless interaction with the vehicle's digital ecosystem significantly affect purchase intentions. This leads to the third hypothesis: **the greater the consumer's experiential involvement, the higher the intention to purchase (H3)**.

Finally, the fourth variable, **Perceived Value**, refers to the subjective balance between perceived benefits and expected costs of adoption. In a context where the cost of purchase and ownership still represents one of the main barriers to electric vehicle adoption, this variable carries significant explanatory power for purchase intention. If consumers perceive the overall value of an electric or hybrid car as greater than its price, they will be more inclined to buy it. Thus, the fourth hypothesis is: **the higher the Perceived Value, the higher the intention to purchase (H4)**.

In addition to the main hypotheses directly linking each independent variable to adoption intention or behaviour, the proposed model also recognizes the existence of **interdependencies** between variables [Figure 12]. These secondary relationships, derived from theoretical analysis, enhance the model's explanatory capacity by offering a more articulated view of the behavioural dynamics underlying technology adoption choices.

One of the most relevant relationships concerns the link between **Technology Appraisal** and **Perceived Value**. If an individual perceives an electric or hybrid vehicle as highly performant, easy to use, safe and aligned with their needs, it is likely they will also assess its cost more favourably. This effect is particularly strong in high-cost contexts such as automotive, where price justification often stems from perceived usefulness, reliability and compatibility with one's lifestyle.

A second significant relationship is found between **Technology Appraisal** and **Consumer Experience Engagement**. A positive user experience, for example, intuitive use of charging apps, easy maintenance, or efficient customer service, can reinforce the belief that the technology is truly accessible and functional. Conversely, the perception of a well-designed and useful technology can raise expectations about the usage experience. The relationship between these two constructs is therefore **bidirectional** and built on the synergy between cognitive expectations and experiential realities.

Consumer Experience Engagement and **Perceived Value** are also logically connected. In many cases, a positive user experience leads to a perception of greater value, even if the economic cost is higher. The investment is justified not only by objective performance but also by the perceived quality of the journey, day-to-day management and after-sales support. This relationship is particularly evident in high-involvement sectors such as automotive, where experience plays a central role in value construction.

Another important interdependency exists between **Socio-Environmental Influence** and **Technology Appraisal**. In the presence of strong social and environmental pressures (e.g., peers supportive of electric mobility, environmental awareness), consumers may reinterpret their cognitive perceptions of the technology more favourably. For instance, exposure to positive narratives about sustainability or direct testimonials from trusted individuals may reduce initial resistance and lead to a perception of the electric vehicle as more functional, reliable, or modern. This aligns with the idea that personal values and social norms act as interpretive frames that also shape technical and rational judgments.

Lastly, a link may also emerge between **Socio-Environmental Influence** and **Perceived Value**. Individuals with strong environmental sensitivity may be more willing to accept higher costs for a sustainable vehicle, assigning greater importance to collective, moral, or symbolic benefits. In this sense, Perceived Value is enriched by an **ethical dimension** that is not always present in consumers who are less sustainability oriented.

In addition to the main and secondary relationships among the theoretical variables, the proposed model also accounts for the possible **moderating effects** of certain sociodemographic characteristics. These moderators do not affect all variables uniformly but may influence specific aspects of the decision-making process more strongly [Figure 12].

Age is a crucial factor in determining openness to new technologies and sensitivity to environmental issues. Younger individuals tend to be more inclined to adopt technological innovations and show greater environmental awareness. However, they may also be more price-sensitive due to limited financial resources. Therefore, age may positively moderate the effect of Technology Appraisal and Socio-Environmental Influence but negatively moderate the effect of Perceived Value.

Gender differences influence priorities and perceptions related to electric vehicle adoption. Men tend to focus more on technical and performance aspects, assigning greater importance to Technology Appraisal and Perceived Value. Women, on the other hand, may be more sensitive to social and environmental influences, showing greater responsiveness to Socio-Environmental Influence and Consumer Experience Engagement.

Driving experience may affect predisposition toward new technologies. More experienced drivers might be less influenced by Consumer Experience Engagement, relying more on rational evaluations based on Technology Appraisal and Perceived Value. Conversely, less experienced drivers may be more responsive to the overall experience offered by the vehicle.

Place of residence (urban vs. rural) may affect access to charging infrastructure and perceptions of electric vehicle utility. Urban residents, with greater access to charging stations and sustainable mobility incentives, may exhibit a stronger Technology Appraisal effect. In contrast, in rural areas, the lack of infrastructure may dampen this effect.

Income influences value perception and price sensitivity. Individuals with higher income are less affected by the initial purchase cost of an electric vehicle, reducing the negative impact of Perceived Value as a financial barrier. However, they may still consider other value aspects, such as environmental benefits and vehicle performance.

A **higher education level** is often associated with greater ability to understand and evaluate new technologies, as well as stronger environmental awareness. Individuals with higher qualifications tend to be more open to adopting electric vehicles, positively moderating the effect of all independent variables, particularly Technology Appraisal and Socio-Environmental Influence.

The empirical data analysis will allow verification of whether and to what extent, these sociodemographic moderators affect the hypothesized relationships, thus further enriching the understanding of the factors that shape technology adoption in the automotive sector.

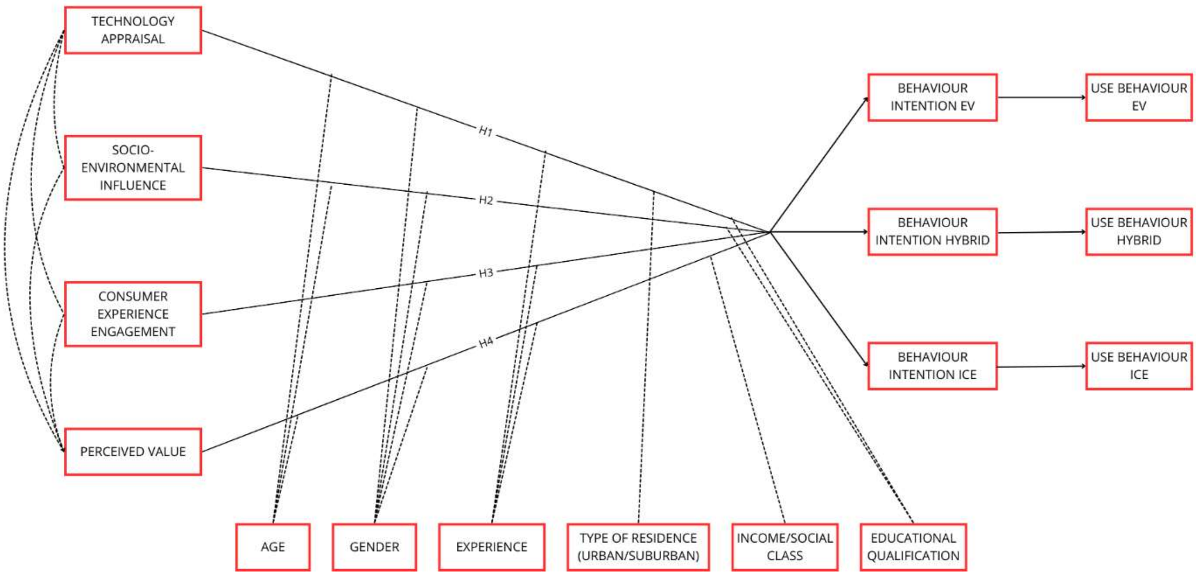

Figure 12: Conceptual model of factors influencing the adoption of electric, hybrid and internal combustion vehicles with hypothesized relationship, interdependencies and moderating effects. Source: Author's elaboration.

5.3. RESEARCH STRATEGY AND QUESTIONNAIRE DESIGN

The construction of the questionnaire represents a central phase of this research project, as it allows the theoretical model developed in the previous chapters (5.1 and 5.2) to be translated into an operational form and used as an empirical tool for data collection [Annex 2]. The main objective of the instrument is to investigate the factors that influence the **intention** and, where relevant, the **usage behaviour** of Italian consumers regarding electric and hybrid cars.

The survey instrument was structured using a 5-point Likert scale (from 1 = "Strongly disagree" to 5 = "Strongly agree") to capture the gradation of respondents' opinions. Each of the four model constructs (Technology Appraisal, Socio-Environmental Influence, Consumer Experience Engagement and Perceived Value) was measured using two or three items, selected to best represent the underlying conceptual dimension through simple, direct and comparative language between electric/hybrid and fuel-powered vehicles. For example, to measure Technology Appraisal, the following item was included: *"I believe that driving a hybrid or electric vehicle would improve my travel efficiency compared to a combustion vehicle."*

The questionnaire is organized into **three main sections**. The first section gathers screening questions and sociodemographic variables. At the beginning, a filter question is presented ("*Do you have a driver's license and regularly drive a car?*"), aimed at selecting only relevant respondents. This is followed by questions on age, gender, education level, type of residence, monthly net household income and years of driving experience. These variables not only allow for a detailed description of the sample but are also essential for analysing the **moderating effects** anticipated in the theoretical model.

Also in the first section, two questions refer to the type of vehicle currently owned (electric, hybrid, or fuel-powered) and any past experience with alternative propulsion vehicles. This information will be crucial for distinguishing usage behaviours based on the technology adopted, allowing for **multi-outcome analysis** and a more nuanced understanding of the adoption phenomenon.

The second section of the questionnaire is entirely dedicated to the measurement of the model's **independent variables**. For each of the four main constructs, questions were formulated using **comparative wording**. For example, regarding Consumer Experience Engagement, the item *"Driving a hybrid/electric vehicle would be a more enjoyable experience than driving a combustion vehicle"* aims to capture perceived experiential quality when comparing different powertrains. For Socio-Environmental Influence, one proposed item is: *"My friends, family, or colleagues would approve of choosing a hybrid or electric vehicle over a combustion vehicle."*

The third and final section is dedicated to measuring **Behavioural Intention**, with the question: *"If I were to buy a new car, I would probably choose an electric or hybrid model."* This wording allows for direct measurement of the model's main outcome. Its simplicity reflects the principle of clear communication, which guided the entire questionnaire design.

Overall, the tool was designed to be easily understandable and accessible, even for non-expert respondents. Special attention was given to **linguistic and conceptual consistency** across questions, the fluidity of the completion process and the clarity of instructions. The use of **examples in parentheses** helped increase semantic precision in more abstract items, facilitating more accurate and informed responses. Moreover, the **sequential structure**, starting from general aspects and moving toward more specific ones, aims to enhance respondent engagement and the quality of the data collected.

5.4. SAMPLING AND REPRESENTATIVENESS CRITERIA

A fundamental phase of this research concerns the definition of the **sampling strategy**, aimed at ensuring both the validity of the results and their generalizability to the Italian population. The theoretical model developed in the previous chapters involves the analysis of psychological, social and behavioural variables, whose impact on the intention to adopt electric or hybrid vehicles may be influenced by sociodemographic characteristics such as age, gender, education level, area of residence, income and driving experience. For this reason, a **proportional stratified sampling** strategy was adopted, based on the most recent data published by ISTAT (2024) [Table 2]. This methodology allows the sample to mirror the proportions observed in the Italian population with respect to the main segmentation criteria.

Although the questionnaire collected information on a broader set of sociodemographic variables (including income, type of residence and driving experience), the comparison with official national statistics (ISTAT) was conducted exclusively for three variables: **gender, age and education**. This decision is based on two main reasons. First, these three dimensions are among the most widely used and stable demographic indicators in behavioural studies and their reliability in large-scale surveys is well documented. Second, gender, age and education are the only variables for which fully up-to-date, detailed and disaggregated data are publicly available and comparable with the categories used in this research. In contrast, variables such as income or driving experience are often subject to inconsistent classification criteria or lack of granularity in national sources, making direct comparison problematic and potentially misleading.

The goal was to construct a sample that would be **as representative as possible** of the Italian population in terms of these dimensions. However, it must be acknowledged that the final sample does not fully meet this criterion. Some deviations emerged during data collection. For example, younger and more educated individuals were overrepresented, while older and lower-educated groups were less present than expected based on national distributions. This discrepancy is likely due to the mode of administration of the questionnaire, which was conducted online and disseminated through digital channels, inherently favouring individuals with greater technological familiarity, higher educational background and more frequent access to online environments.

Despite these imbalances, the inclusion of a sufficiently heterogeneous set of respondents still allows for meaningful segmentation and comparative analysis. Furthermore, the partial deviation from population benchmarks is not unusual in behavioural studies relying on self-administered online surveys and it was mitigated by applying stratified sampling logic during recruitment and by explicitly measuring the sociodemographic moderators in the analysis phase.

The use of gender, age and education as benchmark variables for representativeness allows for a robust and meaningful evaluation of the sample composition. Specifically:

- **Gender**: In the national population, women slightly outnumber men, with official ISTAT data indicating a distribution of **51,3% female** and **48,7% male**. Ensuring a balanced gender representation in the sample is essential to detect any differences in perception or behaviour that may be associated with this variable. Indeed, gender can differently influence perceptions of technology, purchase motivations and the importance attributed to environmental or symbolic values.
- **Age**: it is a well-established predictor of technology adoption. According to ISTAT (2024), the Italian population is distributed as follows: **22,5% between 18 and 34 years old**, **39,8% between 35 and 54**, **29,3% between 55 and 74** and **8,4% over 75 years old**. These proportions were used as a reference when interpreting the age structure of the sample. In line with the objective of capturing opinions and behaviours relevant to car purchasing and usage, only adults with a driving license and who regularly drive were included in the sample.
- **Education**: it plays a significant role in shaping awareness, value systems and openness to innovation. In the 25–64 age range, ISTAT data show that **62,7% of Italians have completed at least upper secondary education**, **10,0% hold a bachelor’s degree** and **10,0% a master’s degree or higher**, while **17,3% have only lower secondary education or less**. These levels were mirrored in the sampling and used as comparison points.

The entire sample structure was thus built according to a logic of **proportionality and representativeness**, both to ensure robust descriptive analyses and to make the interaction tests between sociodemographic variables and the psychological constructs of the model statistically meaningful. In particular, the consistency between the sample structure and the model’s moderators enables a reliable analysis of whether and to what extent, age, gender, education level, residence, or income condition the relationships between the four independent variables and the intention to adopt electric or hybrid vehicles.

The construction of the sample therefore meets a **dual objective**: on the one hand, to provide a solid foundation for statistical analysis, avoiding distortions due to underrepresentation; on the other, to ensure that each reference group is sufficiently large to be analysed as a moderator.

This alignment between methodological design and theoretical structure represents a strength of this study and a necessary condition for the reliability of the conclusions.

Table 2: Italian population distribution (ISTAT 2024). Source: Author's elaboration.

Demographic variable	Category	Population Share (%)
Age	18 - 34 years	22,5%
	35 - 54 years	39,8%
	55 - 74 years	29,3%
	75+ years	8,4%
Gender	Female	51,3%
	Male	48,7%
Education level	Compulsory education	17,3%
	High school diploma	62,7%
	University degree	20,0%

5.5. ANALYTICAL STRATEGY AND SEGMENTATION OF USE BEHAVIOUR

The **methodological phase** of an empirical study plays a crucial role in validating the theoretical model and ensuring the credibility of the results obtained. This section provides a detailed description of the methodological strategy adopted for data collection and analysis, outlining the criteria used in constructing the sample, the **Design of Experiment (DOE)** approach chosen to ensure balance among the analytical categories and the structure of the behavioural outcome, which is divided into three distinct groups. These choices were designed to strengthen the reliability of the study while maximizing the ability to identify significant differences in adoption behaviours and intentions among consumers.

As already outlined in the previous section, the sample was constructed using a **proportional stratified approach**, based on the most recent official data from ISTAT (2024). The main sociodemographic criteria (age, gender and education level) were considered to ensure that the sample reflected the composition of the Italian population. This type of sampling not only allowed for more accurate representation of the population's various segments but also enabled reliable analysis of moderation effects linked to these characteristics.

However, in addition to representativeness, it was also necessary to ensure **balance** among the central analytical categories, namely the groups of users classified according to their vehicle usage behaviour. For this reason, a **balanced Design of Experiment (DOE)** was implemented. The DOE approach, commonly used in the social sciences to plan complex experiments and optimize sample structure, allowed respondents to be assigned to distinct groups in a controlled manner, ensuring an adequate number of participants for each of the target categories. Specifically, a similar number of respondents using, or having used, **electric**, **hybrid** and **fuel-powered vehicles** was ensured, making it possible to conduct comparisons among these three behavioural profiles.

The decision to divide the behavioural outcome into three distinct categories stems from the desire to more comprehensively capture the **complexity** of adoption behaviour in the automotive sector. While most studies focus solely on the general intention to purchase sustainable vehicles, this research proposes a more refined classification that distinguishes between electric vehicle users, hybrid vehicle users and fuel vehicle users (petrol or diesel).

This distinction enables analysis of whether and how, the model variables differentially influence usage intentions and behaviours depending on the adopted technology. For example, it will be possible to assess whether consumer experience has a greater impact on electric vehicle drivers compared to fuel vehicle drivers, or whether environmental value motivations carry more weight among hybrid users. Furthermore, this categorization allows for the exploration of hybrid behavioural patterns, such as the transition from combustion vehicles to more sustainable mobility solutions, a phenomenon increasingly relevant in both the Italian and European contexts.

The questionnaire was designed to collect the information required for this classification: at the end of the sociodemographic section, two questions specifically address the type of vehicle currently used and any past experience with electric or hybrid vehicles. This information makes it possible to segment the sample consistently with the analytical goals and conduct comparative analyses between groups.

The combination of **statistical representativeness** (ensured by ISTAT data), **category balance** (ensured by DOE) and **behavioural outcome segmentation** allows for the development of a **robust methodological framework**, aligned with the complexity of the phenomenon under study. This approach not only adheres to the fundamental principles of quantitative research but also responds to the increasingly recognized need in contemporary literature to adapt research techniques to evolving consumption contexts and ongoing technological transformations.

6. STATISTICAL ANALYSIS AND ITALIAN CONSUMER BEHAVIOUR

After outlining the theoretical model and describing the research methodology, this chapter focuses on the statistical analysis of the data collected through the questionnaire, with the aim of empirically testing the formulated hypotheses and gaining a deeper understanding of Italian consumers' behaviour regarding the adoption of electric and hybrid vehicles. Through a series of quantitative analyses, the chapter aims to examine not only the internal structure of the model, but also the relationships between the theoretical constructs and the sociodemographic characteristics of the respondents.

The chapter begins with the dataset preparation and sample description, assessing the degree of representativeness in relation to the Italian population. This is followed by an examination of the internal consistency of the scales and the latent structure of the variables through factor analysis and reliability indices. A descriptive analysis of the responses and a segmentation by type of vehicle used are then presented, allowing for the identification of initial trends in user behaviour. Attention then turns to the testing of relationships between variables using correlations, ANOVA and multiple linear regression, leading finally to the estimation of a structural equation model (SEM) that integrates all the components under analysis.

Through this process, the chapter aims to validate the proposed theoretical structure and identify the key factors that drive adoption intention. The chapter concludes with a summary of the results and the identification of recurring consumer profiles within the Italian context, providing a solid foundation for the final discussion and the implications that will be developed in Chapter 7 and 8.

6.1. PREPARATION OF THE DATASET AND SAMPLE CHARACTERISTICS

The first phase of the statistical analysis focused on **dataset preparation** and the definition of the **sociodemographic profile** of the collected sample. Starting from the database containing all questionnaire responses, a preliminary check of **data quality** was conducted to ensure consistency, completeness and accuracy. In particular, the presence of empty cells, duplicate responses and formatting errors (e.g., text entered in numeric fields) was verified. Incomplete or invalid observations were removed, resulting in a clean dataset composed of **364 valid respondents**.

The variables included in the questionnaire were coded to be processed in a statistical environment. Sociodemographic variables (age, gender, education, residence, income, driving experience) were converted into ordinal numeric values, consistent with the categories defined in the experimental design. For example, the variable “age” was coded into four levels (1 = 18–34 years, 2 = 35–54 years, 3 = 55–74 years, 4 = over 75 years), while “monthly net household income” was divided into four ranges consistent with the questionnaire structure: under €2.000, €2.000–€2.999, €3.000–€3.999 and over €4.000.

The variables related to the theoretical constructs of the model were also coded using a **5-point Likert scale** (from 1 = “Strongly disagree” to 5 = “Strongly agree”). This coding was applied to the four independent constructs (Technology Appraisal, Socio-Environmental Influence, Consumer Experience Engagement and Perceived Value) and to the dependent variable (Behavioural Intention), following the item assignments defined during the questionnaire construction phase.

To facilitate subsequent analyses, a **variable’s dictionary** was created, reporting for each indicator the technical name, description and coding scheme. This allowed for consistency between the statistical processing phase and the theoretical interpretation [Table 3].

Once the coding and cleaning phases were completed, a **descriptive analysis** of the sample’s sociodemographic profile was carried out, in order to verify its alignment with ISTAT proportions and assess its representativeness. For each moderating variable, absolute and percentage frequencies were calculated and, where possible, compared with official reference data.

In terms of age, the 18–34 age group was overrepresented (42% in the sample versus 22,5% nationally), while the 35–54 (32%) and 55–74 (25%) age groups were slightly underrepresented. Only 1% of the sample was over 75 years old, a figure consistent with the decision to include only regular drivers [Figure 13].

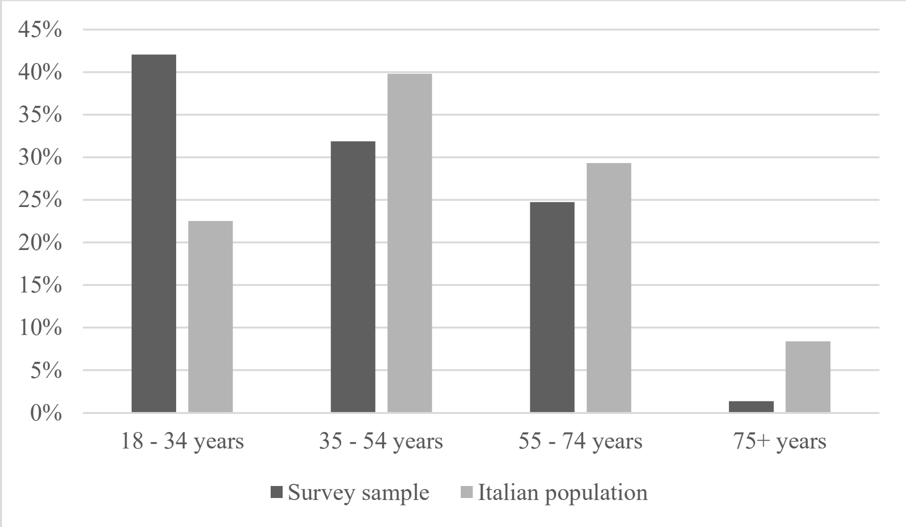

Figure 13: Age distribution comparison: Survey sample vs. Italian population. Source: Author's elaboration.

With regard to gender, the sample consists of 59% male and 41% female respondents. This distribution is slightly unbalanced compared to the Italian population (51,3% female), but it may reflect a greater interest among men in the topic addressed [Figure 14].

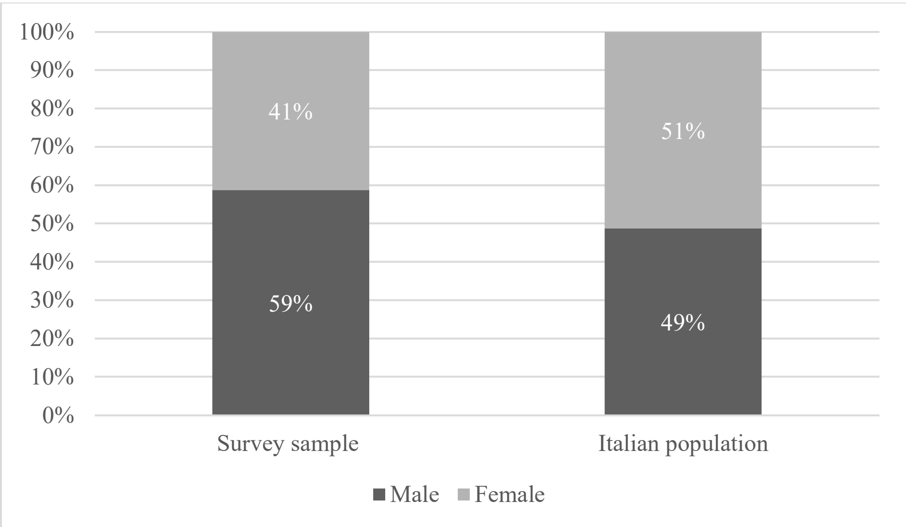

Figure 14: Gender distribution comparison: Survey sample vs. Italian population. Source: Author's elaboration.

In terms of education level, there is a clear prevalence of respondents with a university degree (61%), compared to 20% in the general population. 34% hold a high school diploma, while only 3% of the sample have completed only compulsory education. This distortion is consistent with the voluntary and digital nature of the questionnaire [Figure 15].

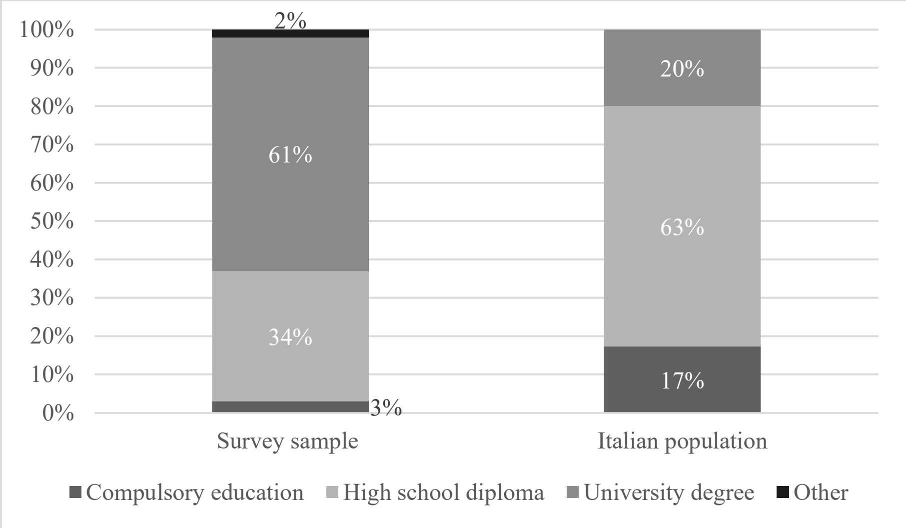

Figure 15: Level of education distribution comparison: Survey sample vs. Italian population. Source: Author's elaboration.

Regarding type of residence, the sample is highly urbanised, with 79% of respondents living in urban areas, compared to 15% in suburban areas and 6% in rural zones. This distribution likely reflects both greater access to digital services and increased awareness of sustainable mobility in cities [Figure 16].

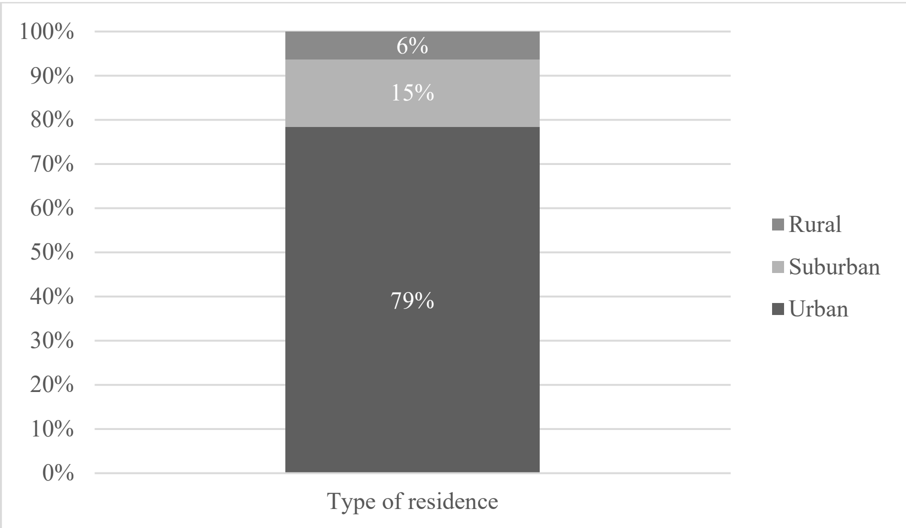

Figure 16: Distribution of respondents by type of residence. Source: Author's elaboration

The distribution of monthly net household income also tends to skew toward middle-to-high income brackets. The most represented ranges are €2.000–€2.999 (27%) and over €4.000 (31%), while 20% of respondents report earning less than €2,000 per month. Another 22% fall within the €3.000–€3.999 range. The distribution is fairly balanced, although it leans toward a moderately high-income level [Figure 17].

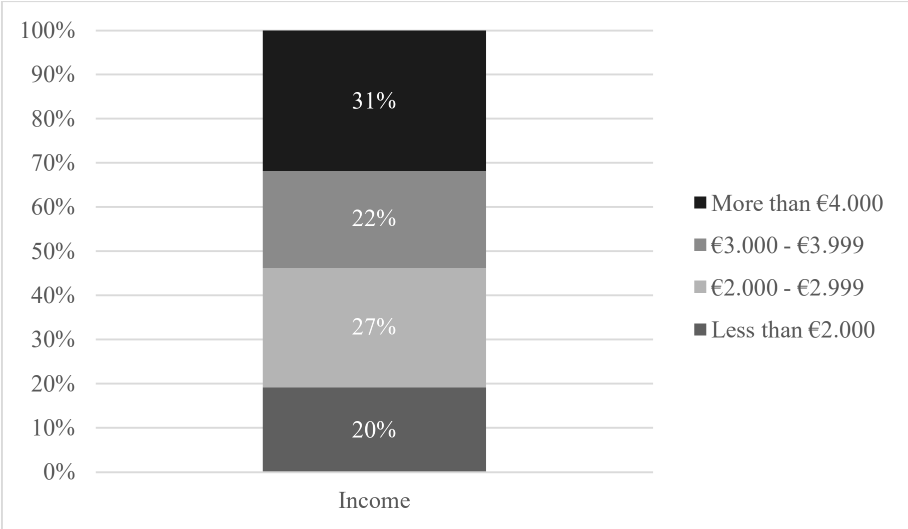

Figure 17: Monthly net household income distribution of the survey sample. Source: Author’s elaboration.

As for driving experience, 52% of respondents have been driving for over 20 years, 29% for 5–10 years, 8% for 11–20 years and 11% for less than 5 years. This data confirms a predominance of experienced and long-term drivers in the sample [Figure 18].

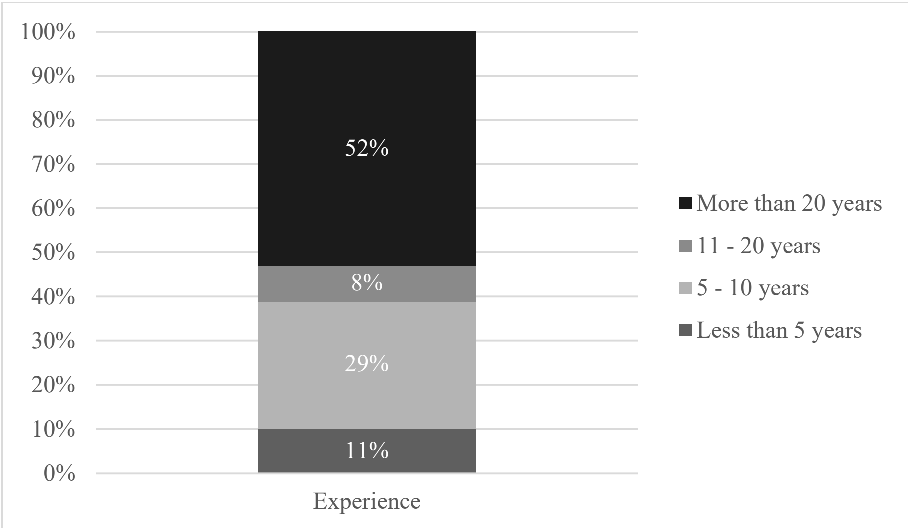

Figure 18: Driving experience distribution among survey respondents. Source: Author’s elaboration.

The distribution of usage behaviour based on the type of vehicle currently driven was also analysed. The sample includes 88% users of internal combustion vehicles (petrol or diesel), 10% hybrid vehicle users and only 2% users of fully electric vehicles. Although unbalanced, this distribution reflects the current proportions of the vehicle fleet in Italy and still allows for segmented analysis [Figure 19].

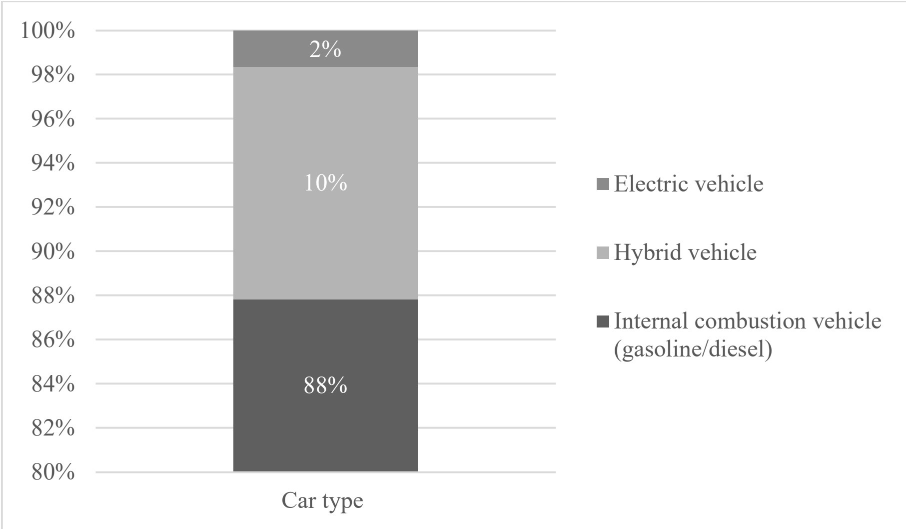

Figure 19: Distribution of current vehicle usage by type. Source: Author's elaboration.

In addition to the type of vehicle most frequently used, previous experience driving electric or hybrid vehicles was also measured, regardless of ownership. 52% of respondents reported having driven a low-emission vehicle at least once, while the remaining 48% had never had this experience [Figure 20].

This information is particularly relevant as it allows for a distinction between consumers who have first-hand familiarity with sustainable mobility and those who maintain a purely theoretical perception of it. For this reason, previous experience will be used as a control variable in the following analyses, in order to assess whether and to what extent, familiarity with new technologies affects users' perceptions and their intention to adopt in the future.

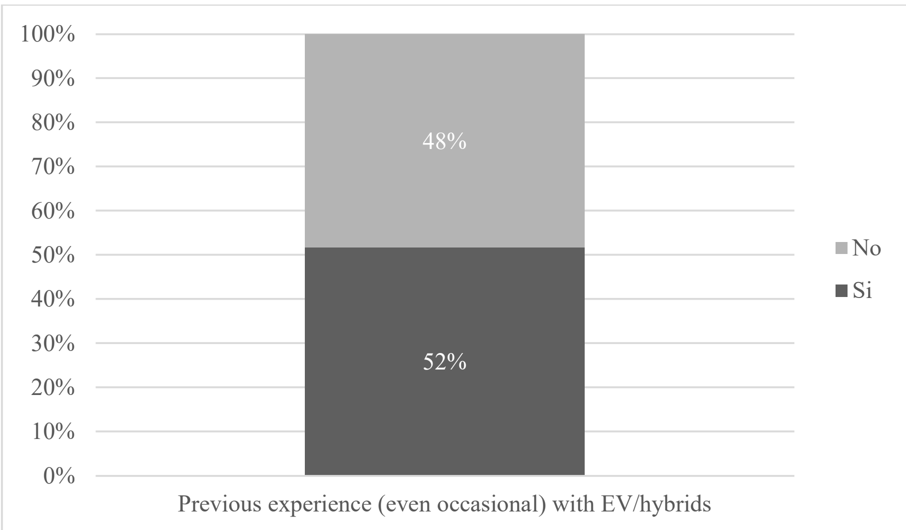

Figure 20: Previous driving experience with electric or hybrid vehicles. Source: Author's elaboration.

Table 3: Variable's dictionary: technical name, description and coding. Source: Author's elaboration.

Variable name	Description	Coding
eta	Age (item 2)	1 = 18–34 years, 2 = 35–54 years, 3 = 55–74 years, 4 = 75+ years
gen	Gender (item 3)	1 = Male, 2 = Female, 3 = Other/Prefer not to answer
ist	Education level (item 4)	1 = Compulsory education, 2 = High school diploma, 3 = University degree, 4 = Other
res	Residence (item 5)	1 = Urban, 2 = Suburban, 3 = Rural
red	Income (item 6)	1 = Less than €2.000, 2 = €2.000-€2.999, 3 = €3.000–€3.999, 4 = More than €4.000
exp	Experience (item 7)	1 = More than 5 years, 2 = 5–10 years, 3 = 11–20 years, 4 = More than 20 years
auto	Car type (item 8)	1 = Internal combustion vehicle (gasoline/diesel), 2 = Hybrid vehicle, 3 = Electric vehicle
elhy	Previous experience EV/Hybrid (item 9)	1 = Yes, 2 = No
ta	Technology Appraisal (item 10, 11, 12)	1 = Strongly disagree, 2 = Somewhat disagree, 3 = Neither agree nor disagree, 4 = Somewhat agree, 5 = Strongly agree
sei	Socio-Environmental Influence (item 13, 14, 15)	1 = Strongly disagree, 2 = Somewhat disagree, 3 = Neither agree nor disagree, 4 = Somewhat agree, 5 = Strongly agree

cee	Consumer Experience Engagement (item 16, 17, 18, 19)	1 = Strongly disagree, 2 = Somewhat disagree, 3 = Neither agree nor disagree, 4 = Somewhat agree, 5 = Strongly agree
pv	Perceived Value (item 20, 21)	1 = Strongly disagree, 2 = Somewhat disagree, 3 = Neither agree nor disagree, 4 = Somewhat agree, 5 = Strongly agree
bi	Behaviour Intention (item 22)	1 = Strongly disagree, 2 = Somewhat disagree, 3 = Neither agree nor disagree, 4 = Somewhat agree, 5 = Strongly agree

6.2. RELIABILITY AND STRUCTURE OF THE SCALES

The second phase of the analysis focused on verifying the **reliability** and **structure** of the theoretical constructs defined in the model. The objective was to assess the internal consistency of the scales built from the questionnaire items and to examine their latent structure through an **Exploratory Factor Analysis (EFA)**. Both analyses are essential for evaluating the quality of measurements and the robustness of the model before proceeding to the next phases of inferential analysis.

6.2.1. INTERNAL RELIABILITY: CRONBACH'S ALPHA

The internal reliability of each construct was estimated using **Cronbach's alpha**, calculated with the *psych* package in R [Table 4]. The values obtained were interpreted according to standard methodological guidelines: values above 0,70 are considered acceptable, values between 0,60 and 0,70 are tolerable in exploratory phases, while values below 0,60 indicate poor reliability.

The results showed good consistency for the Technology Appraisal ($\alpha = 0,78$) and Perceived Value ($\alpha = 0,75$) scales. Both constructs had highly correlated items that contributed coherently to the overall score. In particular, the Perceived Value items, although limited to two, showed a very high inter-item correlation ($r = 0,90$), confirming the conceptual compactness of the scale.

More critical was the Socio-Environmental Influence scale, which had a borderline alpha ($\alpha = 0,60$). Removing item *sei3* raised alpha to 0,70, while *sei2* contributed only marginally.

Although the scale was retained in subsequent analyses, its results should be interpreted with caution. It may be advisable to revise the item wording in future applications to ensure greater clarity and consistency.

The Customer Experience Engagement scale returned a value below the acceptable threshold ($\alpha = 0,55$). Item *cee4* proved particularly problematic, showing weak correlations with the other items and a negative contribution to internal consistency, as identified by R through the check.keys = TRUE option. Removing *cee4* improved alpha to 0,60, leading to the decision to continue the analysis with a "cleaned" version of the scale, including only *cee1*, *cee2* and *cee3*.

Table 4: Reliability analysis: Cronbach's alpha for each item within the measured constructs. Source: Author's elaboration.

Construct	Technology Appraisal			Socio-Environmental Influence			Consumer Experience Engagement				Perceived Value	
Variable name	ta1	ta2	ta3	sei1	sei2	sei3	cee1	cee2	cee3	cee4 (-)	pv1	pv2
Cronbach's alpha	0,71	0,69	0,69	0,43	0,35	0,7	0,44	0,33	0,48	0,6	0,61	0,59

6.2.2. EXPLORATORY FACTOR ANALYSIS (EFA)

To support the reliability analysis, an **Exploratory Factor Analysis (EFA)** was conducted to verify the latent structure of the scales and compare it to the theoretical model. Prior to factor analysis, sample adequacy was assessed with respect to the number and nature of the variables included. Two specific indices were used to evaluate whether the data were suitable for dimensional reduction via factors: the **Kaiser-Meyer-Olkin (KMO)** index and **Bartlett's test of sphericity**.

The **KMO index** returned an overall value of 0,87, which, according to Kaiser (1974), falls into the "meritorious" or "excellent" category (values > 0,80) [Table 5]. The KMO measures the proportion of variance among variables that might be common variance. A high value indicates strong and homogeneous correlations, suitable for identifying stable latent factors. Values below 0,50 would indicate sample inadequacy for factor analysis. The result obtained confirms that the correlational structure of the data is highly compatible with a factor solution.

Table 5: Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy for each variable. Source: Author's elaboration.

Variable name	ta1	ta2	ta3	sei1	sei2	sei3	cee1	cee2	cee3	pv1	pv2
KMO	0,91	0,89	0,92	0,88	0,91	0,92	0,69	0,76	0,90	0,86	0,88

In parallel, **Bartlett's test of sphericity** yielded a chi-square value of 1.462,33, with $p < 0,001$, indicating a significant difference from the null hypothesis. This test verifies whether the correlation matrix is significantly different from an identity matrix (i.e., no correlations). A significant result, as in this case, confirms the presence of strong correlations justifying the use of factor analysis.

The factor analysis was conducted using **Principal Axis Factoring (PAF)** and **Varimax rotation**, testing both a five-factor solution, suggested by parallel analysis [Figure 21], and a four-factor solution consistent with the theoretical framework. Both solutions showed very satisfactory fit indices, in line with commonly accepted methodological thresholds. Specifically, the four-factor solution showed an RMSEA of 0,036 and a TLI of 0,981, while the five-factor solution yielded an RMSEA of 0,033 and the same TLI = 0,981.

The **Root Mean Square Error of Approximation (RMSEA)** reflects how well the model fits the data; values below 0,05 indicate excellent fit, while values between 0,05 and 0,08 are acceptable. The results here are well below the critical threshold, suggesting an excellent fit of the factor structure.

The **Tucker-Lewis Index (TLI)** evaluates the model's improvement over a null model, accounting for complexity. Values above 0,95 indicate excellent fit. The TLI of 0,981 in this case confirms that both tested models represent the latent structure effectively.

Together, these indicators suggest that both models fit the data well. The final choice of the four-factor solution was not based on a difference in fit, since both models performed similarly, but on greater conceptual consistency with the theoretical structure and better interpretability of the factors.

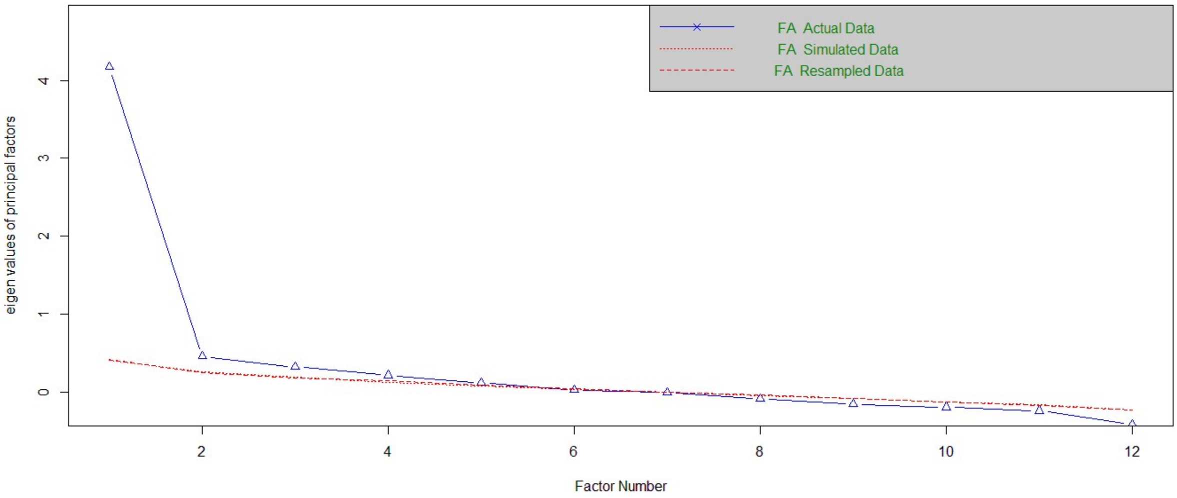

Figure 21: Parallel analysis scree plot for factor retention. Source: Author's elaboration.

Another indicator of EFA quality is the percentage of **total variance explained** by the extracted factors. In this study, the four-factor solution explained 57% of the total variance, a satisfactory result consistent with expectations for research in psychological and social contexts.

Unlike the natural sciences, where variance explanations above 70–80% are common, behavioural and social research often leaves a large portion of variance unexplained due to the complexity of phenomena and presence of unobserved latent variables. Models that explain at least 50–60% of the variance are generally considered acceptable, especially when the identified factors are interpretable and consistent with theory.

In our case, variance was evenly distributed across the four factors, with no single factor dominating the model. This balanced distribution reinforces the idea that each construct contributes significantly to explaining behaviour, increasing the model's stability and validity. Therefore, the 57% explained variance represents a good compromise between parsimony and explanatory power, confirming the adequacy of the factor solution.

The **factor loadings** were found to be consistent with the hypothesised theoretical constructs [Table 6]. In line with methodological literature, an item is considered adequate when it presents a high loading (≥ 0,40 or preferably ≥ 0,50) on a single factor, low loadings (≤ 0,30) on all other factors, indicating semantic purity and explains a sufficient amount of variance, i.e., communality (h^2) ≥ 0.40.

Conversely, certain signals that emerged from the factor analysis should be interpreted as potential indicators of critical issues. For example, when an item has weak loadings (i.e., below

0,30 across all factors), this may suggest poor representativeness with respect to the theoretical construct it was intended to measure. Similarly, the presence of cross-loadings, meaning loadings above 0,40 on multiple factors, may indicate semantic ambiguity or conceptual overlap between different dimensions.

Another red flag arises when an item loads on a factor different from the one theoretically expected (e.g., an item related to user experience loading on the technology factor). This mismatch may be due to unclear wording or a different interpretation by respondents. Lastly, very low communalities ($h^2 < 0,30$) suggest that the item explains only a very small portion of the total variance and may therefore be considered for removal from the model.

In the present case, the items related to Technology Appraisal (*ta1*, *ta2*, *ta3*) loaded clearly on the first factor, confirming good semantic homogeneity. The items related to Perceived Value (*pv1* and *pv2*) also showed high and well-separated loadings on the third factor, with communalities above 0,60, supporting the strength and clarity of the scale.

More evident issues were observed in the Socio-Environmental Influence construct, particularly with item *sei3*, which showed weak loadings across all factors (none above 0,30) and a communality below 0,25, suggesting poor representativeness. Another relevant observation concerns item *cee3*, which, although conceptually linked to user experience, loaded predominantly on the technology factor. This behaviour may reflect semantic overlap or a respondent interpretation more oriented toward the functional dimension than the experiential one.

Table 6: Factor loadings and communalities (h^2) for the extracted components. Source: Author's elaboration.

Item	Technology Appraisal	Socio-Environmental Influence	Consumer Experience Engagement	Perceived Value	h^2
ta1	0,59	0,34	0,18	0,22	0,55
ta2	0,62	0,15	0,22	0,22	0,51
ta3	0,61	0,24	0,15	0,38	0,60
sei1	0,26	0,79	0,14	0,19	0,74

sei2	0,40	0,46	0,12	0,27	0,46
sei3	0,46	0,08	0,08	0,11	0,24
cee1	0,12	0,01	0,96	0,10	0,94
cee2	0,21	0,27	0,56	0,12	0,45
cee3	0,62	0,21	0,07	0,13	0,45
pv1	0,23	0,16	0,11	0,82	0,76
pv2	0,39	0,24	0,13	0,55	0,53

Overall, the results of the analysis support the validity and internal consistency of the adopted scales. The four-factor structure is consistent with the initial theoretical model and meets methodological standards in terms of model fit and explained variance. The critical issues identified with certain items, particularly within the Customer Experience Engagement scale, were addressed through more rigorous item selection and will be further discussed in the concluding chapters.

6.3. DESCRIPTIVE STATISTICS AND PRELIMINARY BEHAVIOUR EVIDENCE

This section aims to systematically describe the distribution of the main variables collected through the questionnaire, by calculating standard descriptive statistics (mean, standard deviation, skewness and kurtosis) and graphically representing the distributions. This type of analysis is a fundamental preliminary step to understand the general behaviour of the sample and to identify any latent trends that will later be tested through inferential statistical tools.

6.3.1. ANALYSIS OF DESCRIPTIVE STATISTICS

All variables were measured using a 5-point Likert scale (from 1 = "Strongly disagree" to 5 = "Strongly agree"). The analysis conducted on the sample (n = 364) revealed **good variability** in the responses, with mean values ranging between 2,43 (*cee4*) and 3,54 (*sei3*) and standard deviations between 1,00 and 1,29 [Table 7]. These values fall well within the expected range for Likert-scale data and indicate the absence of flattening effects or extreme polarisation.

The variable distributions appear globally **symmetric**, as indicated by skewness values between –0,69 and +0,41 and mostly flat, as shown by negative kurtosis values. These descriptive characteristics suggest that responses are evenly distributed across the entire scale and that there are no systematic distortions, ceiling or floor effects, nor abnormal patterns of missing data.

From a content perspective, the item with the highest mean is *sei3* (M = 3,54), which refers to the perception of social self-efficacy, indicating a strong degree of identification with environmental norms and social pressure. On the other hand, lower mean values were observed for *pv1* (M = 2,54) and *ta2* (M = 2,54), related to the perceived economic advantage and effort expectancy, suggesting some concern regarding the accessibility or affordability of the technology.

Table 7: Descriptive statistics for each observed variable. Source: Author's elaboration.

Variable	Mean	Standard deviation	Skewness	Kurtosis
ta1	3,03	1,09	-0,22	-0,68
ta2	2,54	1,07	0,41	-0,54
ta3	2,54	1,00	0,19	-0,46
sei1	3,20	1,02	-0,20	-0,49
sei2	2,82	1,12	-0,17	-0,84
sei3	3,54	1,16	-0,69	-0,40
cee1	2,85	1,29	0,07	-1,35
cee2	2,81	1,08	0,15	-0,85
cee3	3,02	1,16	-0,27	-0,80
pv1	2,54	1,17	0,25	-1,17

pv2	2,91	1,15	-0,13	-1,01

The histogram plot, constructed for four representative items (*ta1*, *sei3*, *cee1*, *pv1*), reinforces these findings [Figure 22]. In particular, item *pv1* shows a distribution skewed toward the lower end, confirming a generally low perceived value, consistent with current data on the still high cost of electric vehicles in Italy. Item *cee1*, related to consumer experience, exhibits clear polarisation, indicating marked differences in satisfaction and service usability among respondents.

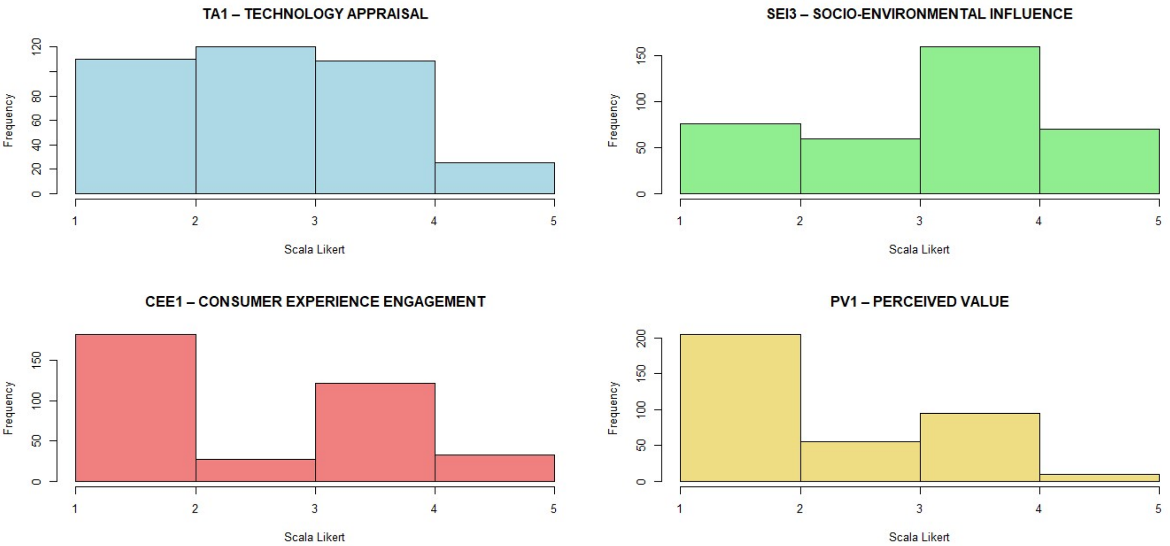

Figure 22: Distribution of responses for selected items on the Likert scale. Source: Author's elaboration.

6.3.2. INITIAL EVIDENCE ON BEHAVIOUR BY VEHICLE TYPE

The sample was segmented based on the type of vehicle currently used: internal combustion engine (ICE), hybrid and electric vehicles. As expected, the majority of respondents (87,9%) reported using a combustion vehicle, while only 10,4% use a hybrid vehicle and 1,6% an electric vehicle. This composition is consistent with data on the circulating car fleet in Italy, where the penetration of electric vehicles is still limited.

Analysing the mean values of the model's key constructs, Technology Appraisal, Socio-Environmental Influence, Consumer Experience Engagement and Perceived Value, in relation to the type of vehicle used, a clear pattern emerges [Table 8]. Electric vehicle users tend to express the **highest evaluations** across all dimensions, suggesting a particularly positive perception of the technology, the user experience and the perceived value. Hybrid vehicle users rank in the **middle**, generally favourable but less markedly so than EV users. Lastly, internal combustion vehicle drivers report **lower average scores** across all constructs and display greater variability in responses, indicating a wider range of perceptions and attitudes within this group. This trend suggests a potential relationship between vehicle type and attitudes toward sustainable mobility, which will be explored further in the comparative analyses that follow.

Table 8: Mean values of key constructs by vehicle type. Source: Author's elaboration.

Car type	**Technology Appraisal**	**Socio-Environmental Influence**	**Consumer Experience Engagement**	**Perceived Value**
Internal combustion vehicle	2,64	3,13	2,84	2,69
Hybrid vehicle	3,07	3,60	3,14	2,89
Electric vehicle	3,67	3,50	4,44	3,17

Boxplot analysis confirms and expands upon the insights derived from the means [Figure 23]. For each construct, the graphical representations show clear differences in **median values** and **response dispersion**.

For Technology Appraisal, electric vehicle users show a higher median, indicating a more positive evaluation of the technology. Their responses are also more concentrated, with a narrower interquartile range (IQR), suggesting more consistent positive perceptions. In contrast, internal combustion vehicle users have a lower median and greater dispersion, indicating more varied and less favourable opinions.

A similar trend is observed for Socio-Environmental Influence. Electric vehicle users attribute more importance to social and environmental influences in their mobility decisions, as indicated by higher medians and more concentrated distributions. This may reflect greater sensitivity to environmental issues and stronger exposure to social networks promoting sustainability.

Regarding Consumer Experience Engagement, electric vehicle users report higher levels of involvement and satisfaction. Their responses are less variable, suggesting generally positive and consistent user experiences. Hybrid users occupy a middle ground, while internal combustion vehicle users show greater variability, indicating more heterogeneous experiences.

Finally, for Perceived Value, electric vehicle users perceive greater value in using their vehicle, with higher medians and more concentrated distributions. This could be attributed to perceived benefits such as fuel cost savings, tax incentives, or satisfaction from adopting sustainable technologies.

In summary, the boxplot analysis suggests that electric vehicle usage is associated with more positive and consistent perceptions regarding technology, socio-environmental influence, consumer experience and perceived value. The boxplots therefore offer a complementary perspective to the numerical data, reflecting not only average agreement levels but also the consistency of perceptions within each group.

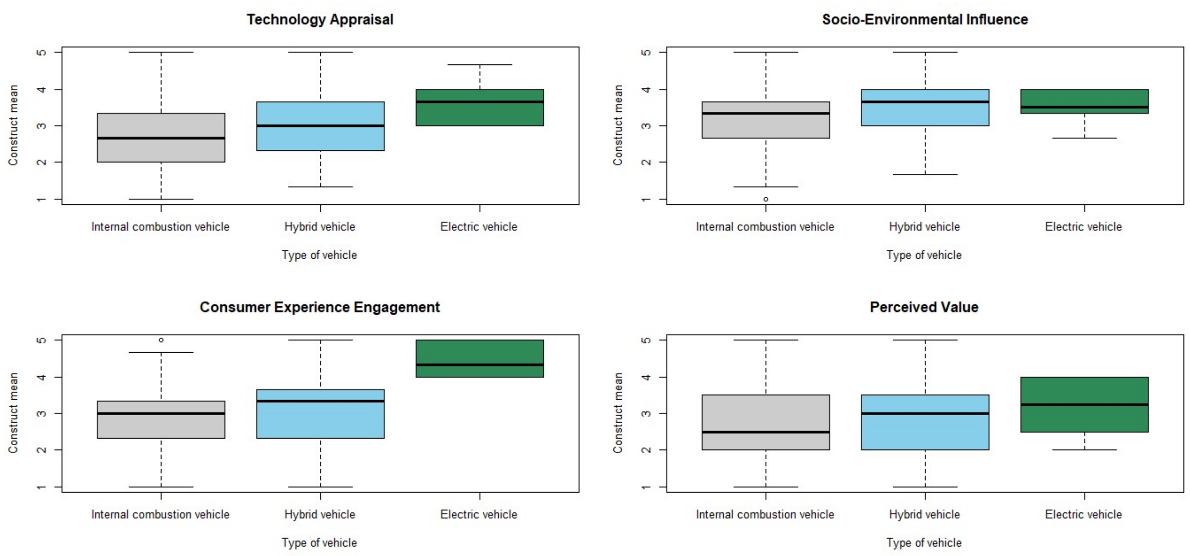

Figure 23: Boxplots of construct means by vehicle type. Source: Author's elaboration.

These initial behavioural findings indicate that the adoption of low-emission vehicles is associated with more favourable perceptions of technology, perceived value and user experience. The data also suggest that previous experience and actual usage of an electric or hybrid vehicle may positively impact the cognitive and emotional evaluation of new technologies. This aspect will be explored in more depth in the subsequent inferential analyses (ANOVA, regression) to assess statistical significance.

6.4. CORRELATIONS BETWEEN MODEL VARIABLES

The analysis of correlations among the theoretical constructs of the model represents a key step in assessing its internal coherence, conceptual independence and predictive relevance with respect to the dependent variable. For this purpose, a **Pearson correlation matrix** was computed among the four independent variables [Table 9]. All constructs were treated as continuous variables, aggregated from their respective items, in line with established psychometric practices.

The results reveal a network of **positive**, statistically significant and moderate-to-strong correlations, with coefficients ranging from 0,41 to 0,64. The strongest correlation is found between Technology Appraisal and Socio-Environmental Influence (r = 0,64), suggesting that a positive evaluation of the technology often goes hand in hand with greater sensitivity to social norms and environmental issues. This association is well documented in the literature, where trust in technology and perceived usefulness are shown to reinforce environmental responsibility and adherence to pro-sustainability social norms.

Technology Appraisal also shows a substantial correlation with Perceived Value (r = 0,60), confirming that technologies perceived as reliable, useful and easy to use also tend to be seen as more convenient in terms of overall cost-benefit. The link between Consumer Experience Engagement and Perceived Value is lower (r = 0,41), yet still significant, reflecting the role of user experience in shaping overall economic evaluations. All values remain well below the 0,80 threshold, ruling out multicollinearity issues and confirming construct discriminant validity, i.e., their ability to capture distinct theoretical concepts.

Table 9: Pearson correlation coefficients among latent constructs. Source: Author's elaboration.

	Technology Appraisal	**Socio-Environmental Influence**	**Consumer Experience Engagement**	**Perceived Value**
Technology Appraisal	1,00	0,64	0,58	0,60

Socio-Environmental Influence	0,64	1,00	0,48	0,51
Consumer Experience Engagement	0,58	0,48	1,00	0,41
Perceived Value	0,60	0,51	0,41	1,00

In addition to the model's internal consistency, the **correlation** between each of the four independent variables and the dependent variable Behavioural Intention was also analysed [Table 10]. Once again, the results confirm positive, significant and theoretically grounded associations.

In particular, Technology Appraisal shows the strongest correlation with intention (r = 0,62), suggesting that perceptions of efficiency, simplicity and reliability are key determinants of adoption propensity. This finding is consistent with prior research based on the TAM and its extensions, where perceived usefulness is recognised as a primary driver of usage intention.

Socio-Environmental Influence (r = 0,57) and Perceived Value (r = 0,55) also show moderate-to-strong relationships with behavioural intention, suggesting that social context and perceived cost-benefit act as important motivational factors in the consumer's decision-making process. Finally, Consumer Experience Engagement shows a significant correlation (r = 0,50), confirming that the quality of the user experience, including ease of access, enjoyment and continuity of interaction, plays a relevant role in guiding adoption decisions, particularly in the context of emerging technologies.

Table 10: Pearson correlations between latent constructs and behavioural intention. Source: Author's elaboration.

Construct	r with Behavioural Intention
Technology Appraisal	0,62
Socio-Environmental Influence	0,57
Consumer Experience Engagement	0,50

Perceived Value	0,55

Overall, the correlation analysis consistently supports the convergent **validity** of the theoretical model and provides initial empirical evidence of the relevance of the four independent variables in explaining behavioural intention. These findings justify proceeding to a predictive analysis phase, such as multiple linear regression, which will be addressed in Chapter 6.6.

6.5. ANOVA AND SEGMENTATION OF USER PROFILES

The **Analysis of Variance (ANOVA)** was used to explore whether the main constructs of the model vary significantly across different user groups, both in terms of sociodemographic characteristics and according to the type of vehicle currently used. This approach allows the identification of systematic differences in consumer perceptions and behaviours, enabling more targeted segmentation.

Before proceeding with ANOVA, the necessary assumptions for its validity were tested [Table 11]. First, the **independence of observations** is ensured by the mode of questionnaire administration. The **normality** of the distributions was initially assessed using the Shapiro-Wilk test. The results show that none of the four main variables fully meets the assumption of normality ($p < 0,05$ in all cases). However, according to the literature, ANOVA is considered robust against moderate violations of normality, particularly when a large sample size ($n > 200$) and similarly sized groups are available, both of which are met in this case.

To support this assessment, a Q-Q plot of residuals was also performed for each construct [Annex 1]. The points tend to follow the theoretical line, with limited deviations in the tails, suggesting that although deviations from normality are statistically significant, they do not substantially compromise the analysis.

The **homogeneity of variances** was assessed using Levene's Test, which in no case detected significant differences between group variances ($p > 0,25$), thereby confirming the assumption of equal variances. However, a more detailed graphical analysis reveals a potential issue: the standardized residuals plotted against predicted values show a fan-shaped or inverse pattern, where the residuals are not randomly scattered around the red line (representing null residuals) but rather follow a well-defined diagonal arrangement [Annex 1]. This structure may indicate heteroscedasticity, meaning a non-constant error variance across predicted values and could reflect that the model does not fully capture the underlying data structure.

In conclusion, although the residual plots suggest a possible violation of the homoscedasticity assumption, the results from Levene's Test do not show significant differences between group variances. Since the statistical test is generally considered more reliable than graphical inspection, it is deemed that the assumption of equal variances is overall met. Therefore, the use of **ANOVA is considered appropriate**.

Table 11: Levene's test and Shapiro-Wilk test results for construct assumptions. Source: Author's elaboration.

Construct	Shapiro-Wilk (p)	Levene's Test (p)
Technology Appraisal	1,57e-05	0,487
Socio-Environmental Influence	7,89e-06	0,490
Consumer Experience Engagement	0,00013	0,251
Perceived Value	2,36e-09	0,607

The analysis continued by testing the **effect of sociodemographic variables** on each construct. The results show that gender is significantly associated with all four constructs ($p < 0,01$), suggesting that men and women develop different perceptions concerning technology, user experience, perceived value and social influence [Table 12]. These differences are consistent with previous literature: men tend to place greater emphasis on technological performance, whereas women are generally more sensitive to relational, value-based and environmental dimensions.

Age also significantly affects Socio-Environmental Influence ($p = 0,011$) and especially Perceived Value ($p < 0,001$), where a gradual decrease in economic evaluation is observed with increasing age. This aligns with studies showing that younger individuals tend to perceive higher value, likely due to greater openness to change and less attachment to conventional mobility costs. Education level shows a marginal association with Socio-Environmental Influence ($p = 0,044$), as does household income ($p = 0,045$). Driving experience, however, has a strong impact on Perceived Value ($p < 0,001$), indicating that less experienced drivers tend to assign higher value, possibly due to less exposure to traditional models.

*Table 12: Significance levels (p-values) for the relationships between socio-demographic variables and latent constructs. Statistically significant values (p < 0,05) are marked with ★, while marginally significant values (p < 0,10) are indicated with *. Source: Author's elaboration.*

Variable	Technology Appraisal	Socio-Environmental Influence	Consumer Experience Engagement	Perceived Value
Gender (gen)	0,0003 ★	6,7e-06 ★	0,0017 ★	2,95e-07 ★
Age (eta)	0,146	0,0111 ★	0,883	4,55e-09 ★
Education (ist)	0,284	0,0443 ★	0,246	0,146
Residence (res)	0,252	0,750	0,055 *	0,217
Income (red)	0,117	0,0454 ★	0,453	0,617
Driving experience (exp)	0,189	0,0783 *	0,395	3,26e-09 ★

6.5.1. SEGMENTATION BY VEHICLE TYPE

A further ANOVA test was conducted using the **type of vehicle currently used** as the independent variable (internal combustion, hybrid, electric), with the four psychological constructs as dependent variables. The results indicate significant differences for three out of the four constructs analysed [Table 13].

The mean scores for Technology Appraisal (p = 0,0004) are significantly higher among electric and hybrid vehicle users than combustion vehicle users. Regarding Socio-Environmental Influence (p = 0,0027), the highest scores are recorded among hybrid vehicle drivers, while Consumer Experience Engagement (p < 0,0001) shows the largest variation: electric vehicle users report significantly higher engagement levels than all others.

In contrast, the construct Perceived Value does not show statistically significant differences across groups (p = 0,305), suggesting that cost-benefit perception is not systematically influenced by the type of vehicle used.

Table 13: ANOVA results: Differences in construct means by vehicle type. Source: Author's elaboration.

Construct	ANOVA p-value
Technology Appraisal	0,0004
Socio-Environmental Influence	0,0027
Consumer Experience Engagement	6,8e-06
Perceived Value	0,305 (ns)

6.5.2. POST-HOC COMPARISONS

To explore group differences in more detail, **post-hoc Tukey tests** were conducted [Table 14]. The results confirm that electric vehicle drivers attribute significantly higher scores to Technology Appraisal than internal combustion users ($\Delta = +1{,}03$; $p = 0{,}011$) and report much higher Consumer Experience Engagement compared to both combustion ($\Delta = +1{,}61$; $p < 0{,}001$) and hybrid users ($\Delta = +1{,}30$; $p = 0{,}002$). Hybrid vehicle users also report more favourable evaluations of Technology Appraisal ($\Delta = +0{,}43$; $p = 0{,}011$) and Socio-Environmental Influence ($\Delta = +0{,}46$; $p = 0{,}003$) than combustion vehicle users.

These findings suggest that direct experience with low- or zero-emission vehicles contributes to reinforcing positive attitudes toward sustainable mobility and its associated technologies. The absence of significant differences in Perceived Value can be interpreted in light of the fact that, despite perceived benefits, actual costs still represent a cross-cutting barrier to adoption.

Table 14: Post-hoc comparisons of construct means by vehicle type. Source: Author's elaboration.

Construct	Group Comparison	Mean Difference	p-value
Technology Appraisal	EV – Combustion	+1,03	0,011
	Hybrid – Combustion	+0,43	0,011
Socio-Environmental Influence	Hybrid – Combustion	+0,46	0,003

Consumer Experience Engagement	EV – Combustion	+1,61	<0,001
	EV – Hybrid	+1,30	0,002
Perceived Value	No significant comparison	–	>0,30

6.6. HYPOTHESIS TESTING THROUGH REGRESSION

To test the direct hypotheses regarding the relationships between the psychological constructs identified in the theoretical model and the behavioural intention to adopt electric or hybrid vehicles, a **multiple linear regression analysis** was conducted. The dependent variable (Behavioural Intention) was modelled as a linear function of four independent variables: Technology Appraisal, Socio-Environmental Influence, Consumer Experience Engagement and Perceived Value.

The model was statistically **significant** ($F(4, 359) = 84{,}43$, $p < 0{,}001$) and explained 48,5% of the variance in adoption intention ($R^2 = 0{,}485$; adjusted $R^2 = 0{,}479$), which is a high value for behavioural studies, where response variability is often affected by unmeasured latent factors. All predictors were significant at $p < 0{,}001$, confirming hypotheses H1–H4 of the model [Table 15].

Specifically, Technology Appraisal showed the highest coefficient ($\beta = 0{,}365$; $p < 0{,}001$), indicating that a positive perception of the technology in terms of usefulness, ease of use and reliability is a key driver of purchase intention. This result is consistent with the technology acceptance literature (TAM and UTAUT), where Performance Expectancy is traditionally the strongest predictor of intention.

Socio-Environmental Influence ($\beta = 0{,}306$; $p < 0{,}001$) was also a significant predictor. This suggests that the influence of social norms, environmental values and moral perceptions has a real impact on the decision-making process. This effect is consistent with integrative models such as the Norm Activation Model (NAM), which highlights the role of personal and collective norms in pro-environmental behaviours.

The contribution of Consumer Experience Engagement ($\beta = 0{,}219$; $p < 0{,}001$) reflects the importance of the user experience in the evaluation of a new technology. In line with customer experience literature, the ease of interaction with services, personal gratification and familiarity developed over time help shape a favourable attitude and more stable intentions.

Finally, Perceived Value ($\beta = 0{,}266$; $p < 0{,}001$) proved to be a key dimension, showing how the balance between perceived benefits and economic costs significantly influences the likelihood of purchase. This finding aligns with the model of Zeithaml (1988), which states that value perception broadly conditions consumer choices.

All coefficients were also examined in **standardised** form to directly compare the relative impact of the predictors, regardless of unit scales. The strongest effect was attributed to Technology Appraisal (β standardised = 0,262), followed by Perceived Value (β = 0,227), Socio-Environmental Influence (β = 0,206) and Consumer Experience Engagement (β = 0,158). These results suggest that cognitive aspects (related to technological functionality) and economic evaluations are the main drivers of adoption intention, while user experience and social pressure play significant but secondary roles.

Residual diagnostics ruled out multicollinearity issues, with all VIF values below 2,5, well under critical thresholds. This confirms the statistical independence of the variables and the stability of the model.

Table 15: Multiple linear regression results: Predictors of behavioural intention. Source: Author's elaboration.

Independent Variable	β Coefficient	Standardised β	Std. Error	t-value	p-value
Technology Appraisal	0,365	0,262	0,080	4,54	7,67e-06
Socio-Environmental Influence	0,306	0,206	0,076	4,02	7,13e-05
Consumer Experience Engagement	0,219	0,158	0,066	3,35	0,0009
Perceived Value	0,266	0,227	0,057	4,69	3,82e-06

6.6.1. MODERATION EFFECTS OF SOCIO-DEMOGRAPHIC VARIABLES

To test the possible influence of sociodemographic variables on the relationship between psychological constructs and behavioural intention, **interaction regression models** were constructed. These included product terms between the main predictors and the moderators: age, education, driving experience, residence, income and education.

The results show that no interaction terms reached statistical **significance** at the conventional $p < 0,05$ level [Table 16]. However, some marginal effects ($p < 0,10$) warrant attention. Specifically, the interaction between Technology Appraisal and the age group 55–74 years (category 3) had a positive coefficient ($\beta = 0,266$; $p = 0,056$), suggesting that in this age group, appreciation for technology may have a slightly stronger impact on adoption intention.

Similarly, the interactions between Perceived Value and driving experience (categories 2 and 3: 5–10 years and 11–20 years) returned marginal p-values (0,077 and 0,090, respectively), indicating that greater driving experience may amplify the effect of perceived value. Although not conclusive, these results align with literature suggesting that expertise may moderate the weight attributed to perceived cost-benefit assessments.

Overall, these data do not provide strong support for moderation effects, but they suggest trends that could be further explored in future studies with larger and more balanced samples.

Table 16: Moderation analysis: Interaction effects between demographic variables and main constructs. Source: Author's elaboration.

Moderator	Moderated Construct	Coefficient β	p-value
Age	TA × Age3	0,266	0,056
Experience	PV × Experience2	≈ 0,25	0,077
	PV × Experience3	≈ 0,34	0,09

6.7. STRUCTURAL EQUATION MODELLING (SEM)

After empirically validating the model's hypotheses through multiple linear regression, a **Structural Equation Modelling (SEM)** analysis was conducted to simultaneously test the structure of the theoretical relationships between latent constructs and their observed variables. This approach enables a more comprehensive model evaluation, integrating both the measurement dimension (scale validity and reliability) and the structural dimension (relationships among constructs) within a unified statistical framework.

The proposed SEM model includes four latent constructs (Technology Appraisal, Socio-Environmental Influence, Consumer Experience Engagement and Perceived Value) and one latent dependent variable, Behavioural Intention. Each construct is measured by the corresponding items derived from the questionnaire, previously validated in earlier analyses.

The estimated model is **saturated** (i.e., overidentified), meaning it has no degrees of freedom. In such cases, fit indices return perfect values: RMSEA = 0,000, SRMR = 0,000, CFI = 1,000, TLI = 1,000. These values indicate a perfect match between the model and the observed data. However, it is important to note that in saturated models, fit indices have limited informational value, as the model is structured to reproduce the observed covariance matrix exactly. Nevertheless, the fact that the estimation converges and the parameters are statistically significant is a positive sign of internal consistency.

The analysis results show that all four latent constructs exert a positive and statistically **significant** direct effect on adoption intention [Table 17]. Technology Appraisal has the strongest effect ($\beta = 0{,}365$, $p < 0{,}001$), confirming the central role of perceived usefulness, efficiency and trust in technology as predictors of intention. This finding aligns with TAM and its extensions, in which performance expectancy is consistently associated with increased adoption propensity.

Socio-Environmental Influence also has a substantial effect ($\beta = 0{,}306$, $p < 0{,}001$), suggesting that social context, moral norms and identification with environmental values directly influence consumer behaviour. Perceived Value ($\beta = 0{,}266$, $p < 0{,}001$) is confirmed as a significant predictor, consistent with perceived value theory, which holds that the balance between benefits and costs guides consumption intentions. Finally, Consumer Experience Engagement is also significant ($\beta = 0{,}219$, $p = 0{,}001$), indicating that the quality of technological interaction, regarding ease, gratification and habit, plays a role, albeit smaller.

The standardised coefficients (Std.all) confirm the effect hierarchy: Technology Appraisal remains the strongest predictor (β = 0,262), followed by Perceived Value (β = 0,227), Socio-Environmental Influence (β = 0,206) and Consumer Experience Engagement (β = 0,158). These results closely mirror those obtained through linear regression, reinforcing their validity.

Table 17: Direct effects on behavioural intention: Unstandardised and standardised coefficients. Source: Author's elaboration.

Path	β Coefficient	Standardised (Std.all)	p-value
TA → BI	0,365	0,262	$p < 0{,}001$
SEI → BI	0,306	0,206	$p < 0{,}001$
CEE → BI	0,219	0,158	$p = 0{,}001$
PV → BI	0,266	0,227	$p < 0{,}001$

The SEM analysis also allowed for the investigation of **indirect relationships** between constructs, offering a more nuanced understanding of the decision-making mechanism [Table 18]. Specifically, Consumer Experience Engagement influences behavioural intention indirectly through Technology Appraisal (β = 0,348, p < 0,001) but does not exert a direct effect on Perceived Value (β = 0,069, p = 0,240), suggesting that user experience does not directly affect economic value perception but operates primarily through technological evaluation.

By contrast, Socio-Environmental Influence shows significant effects on both Technology Appraisal (β = 0,508, p < 0,001) and Perceived Value (β = 0,269, p < 0,001), indicating that environmental values and social pressure not only influence intention directly but also indirectly by reshaping technological and economic perceptions. The Technology Appraisal - Perceived Value path is also significant (β = 0,505, p < 0,001), confirming the hypothesis that a strong technological evaluation enhances perceived value, as discussed in technological marketing literature.

Table 18: Indirect and mediation paths among constructs: Unstandardised and standardised coefficients. Source: Author's elaboration.

Path	β Coefficient	Standardised (Std.all)	p-value
CEE → TA	0,348	0,348	$p < 0{,}001$
SEI → TA	0,508	0,477	$p < 0{,}001$
TA → PV	0,505	0,425	$p < 0{,}001$
CEE → PV	0,069	0,058	$p = 0{,}240$
SEI → PV	0,269	0,212	$p < 0{,}001$

The SEM model explains 48,5% of the **variance** in Behavioural Intention ($R^2 = 0{,}485$), a high value in behavioural research, particularly satisfactory for studies on complex phenomena such as the adoption of sustainable technologies [Table 19]. It also explains 50,8% of the variance in Technology Appraisal ($R^2 = 0{,}508$) and 38,6% in Perceived Value ($R^2 = 0{,}386$), confirming the model's capacity to capture the underlying structure of consumer perceptions and evaluations.

Table 19: Explained variance (R^2) for key endogenous constructs in the SEM model. Source: Author's elaboration.

Variable	R^2
Behavioural Intention	0,485
Technology Appraisal	0,508
Perceived Value	0,386

Overall, the SEM provides consistent, robust and theoretically grounded evidence for the role of the four model dimensions in predicting adoption intention. The convergence between regression and SEM results enhances the credibility of the conclusions and strengthens the validity of the adopted theoretical framework.

6.8. SUMMARY OF RESULTS AND CONSUMER PROFILES

The analytical process developed in this chapter made it possible to thoroughly examine the factors influencing Italian consumers' intention to adopt electric and hybrid vehicles. The integration of various statistical techniques, from descriptive analysis to regression, ANOVA and structural modelling, produced a coherent, robust and multi-layered framework capable of empirically validating the proposed theoretical model.

Among the main findings, the **central** role of Technology Appraisal is confirmed as the strongest predictor of behavioural intention. Users who perceive electric technology as useful, reliable, compatible with their needs and easy to use show a significantly higher propensity to adopt it. This result is fully consistent with the predictions of major technology acceptance models such as TAM and UTAUT2 and underscores the importance of trust in and understanding of technology as enabling factors.

The value and socially driven dimension (Socio-Environmental Influence) also demonstrated a strong impact, both directly and indirectly. Environmental awareness, a sense of personal responsibility and the influence of social networks appear to act as important motivational factors, especially among those who identify with ecological values or who perceive positive pressure from their social environment. These findings confirm the relevance of normative and value-based theories, such as NAM, in interpreting sustainable consumption behaviour.

Customer experience and experiential engagement (Consumer Experience Engagement) are more relevant insofar as they affect perceptions of the technology. Their indirect effect, mediated through Technology Appraisal, suggests that positive interaction with services associated with the vehicle (e.g., charging apps, digital assistance, ease of use) contributes to strengthening adoption intentions. However, their direct impact appears more limited compared to other constructs, indicating that user experience alone is not sufficient to trigger purchasing behaviour but serves as a complementary lever.

Perceived Value emerges as a key factor. The perception of a favourable cost-benefit ratio significantly influences purchase propensity, reaffirming the centrality of economic evaluation in the decision-making process. However, the data suggest that this dimension is less sensitive to group differences: despite its positive effect on the dependent variable, Perceived Value appears relatively homogeneous across users of different technologies, highlighting that price remains a widespread cross-cutting barrier in the Italian context.

From a **sociodemographic perspective**, the analysis revealed some notable differences. Younger consumers tend to place greater importance on technological innovation and show a higher predisposition to adopt. On average, women are more sensitive to environmental and social aspects, whereas men tend to place more value on performance and economic aspects. Education level and driving experience partly modulate the effect of independent variables, without altering their direction. In particular, more experienced drivers seem to attribute more importance to the economic aspect and less to the experiential one.

Lastly, the **behavioural segmentation** based on the type of vehicle currently used provided an interesting perspective. Electric vehicle users systematically expressed higher evaluations on all constructs analysed, followed by hybrid vehicle users, while internal combustion engine drivers reported lower values and greater heterogeneity in their responses. This difference suggests that direct experience with the technology plays an important role in consolidating favourable attitudes, fuelling a virtuous cycle between usage, trust and predisposition to repurchase.

In summary, the results outline the profile of an Italian consumer who is increasingly attentive to technological quality, sensitive to environmental values, but still influenced by economic evaluations and not always satisfied usage experiences. The proposed model has proven solid and effective in capturing the **psychological, social** and **economic determinants** behind the adoption of sustainable vehicles. The evidence collected provides a solid empirical foundation for the discussion and implications that will be explored in Chapter 7.

7. CRITICAL DISCUSSION AND PRATICAL IMPLICATIONS

This study made it possible to explore the main factors that influence Italian consumers' intention to adopt electric, hybrid, or internal combustion vehicles, by combining the theoretical framework of technology acceptance models with constructs related to customer experience and sustainability.

Moreover, the analysis offers several practical implications for stakeholders in the automotive market, particularly car manufacturers, policymakers and operators in the sustainable mobility sector. The findings suggest that the adoption of electric and hybrid vehicles does not solely depend on technological or economic variables, but rather on a complex interplay of **perceptions**, **experiences** and **social influences**. These findings also reflect certain characteristics specific to the Italian context, which deserve critical consideration.

Firstly, the analysis confirmed the central role of the Technology Appraisal construct in predicting behavioural intention, as already highlighted by studies conducted in other European and Asian countries. However, the strong impact of this variable in the sample analysed also reflects a growing sensitivity towards the **perceived quality** of new technological solutions and trust in their reliability, especially in relation to electric mobility. Compared to other contexts, the Italian data suggest that consumers are increasingly willing to assess the efficiency and practicality of alternative vehicles, provided that concerns about **range**, **infrastructure** and **maintenance** are adequately addressed. This highlights the importance of investing in **experiential marketing strategies** and **educational communication** to overcome perceptual barriers often linked to lack of knowledge or unjustified fears.

The Socio-Environmental Influence construct, which emerged among the strongest predictors in both regression and SEM models, is widely supported by the literature highlighting the impact of subjective norms and value systems on purchase behaviour. This aspect becomes even more relevant in a country like Italy, where the adoption of sustainable behaviours is often shaped by the **social environment** and **local awareness campaigns**. Normative pressure and the social visibility of pro-environmental behaviour, particularly among younger people, appear to function as important motivational levers. Therefore, corporate strategies should integrate narratives centred on environmental responsibility, ecological footprint reduction and **positive emulation effects**. Advertising campaigns, incentive programs and educational initiatives should leverage the role of **social norms** and **opinion leaders** to accelerate the **normalisation of electric mobility** in consumers' daily lives.

The results related to Customer Experience Engagement also underscore the growing importance of the experiential dimension, in line with theories by Holbrook & Hirschman (1982) and more recent work on **experience innovation** (Solis, 2019). Users who perceive the interaction with the brand and the use of the vehicle as engaging, consistent and positive are more likely to choose alternatives to internal combustion. This finding highlights the need for companies to invest in **personalised journeys** and **memorable usage experiences**, as these elements significantly contribute to **perceived value**.

The Perceived Value construct acts as a bridge between rationality and emotion: consumers evaluate the balance between costs (economic, logistical, emotional) and benefits (savings, status, alignment with values). Its relative importance confirms that, even in the presence of increasing environmental awareness, economic criteria remain central to purchase decisions.

This is consistent with what has been stated by Venkatesh et al. (2012) and Rezvani et al. (2015), who argue that perceived value synthesises utility, price, status and overall satisfaction. Companies should therefore focus on making the benefits tangible, not only through public incentives but also via flexible pricing policies, extended warranties and value-added services (such as software updates and smart assistance).

An additional area of reflection involves **segmentation by socio-demographic variables**, allowing for more targeted promotional actions. Young people, individuals with medium-high income, higher education and urban residence tend to be more open to low-emission technologies; for these segments, communication should focus on innovation, value and sustainability. For more resistant groups (elderly people, rural residents, low-income individuals), it is advisable to develop supportive policies, for example through tax incentives, widespread infrastructure and ecological transition education programs.

Lastly, **methodological and contextual aspects** must also be considered. The model demonstrated a good fit to the data and the hypothesised relationships were statistically significant; however, not all variables had the same impact. This suggests that, while UTAUT2 and customer-based models are solid, their application in the Italian market requires **adaptation**, particularly to capture the **cultural**, **infrastructural** and **economic specificities** of the context.

8. CONCLUSIONS, LIMITATIONS AND FUTURE RESEARCH

This final chapter summarizes the main findings of the research, offering a critical reflection on the process undertaken and the resulting implications. After analysing the behaviour of Italian consumers regarding the adoption of electric and hybrid vehicles through an integrated and empirically validated theoretical model, a comprehensive reflection is now proposed.

The chapter opens with a general conclusion that assesses the degree to which the initial objectives were achieved, linking the findings to the original research questions. This is followed by a section on the study's limitations, highlighting the main methodological and conceptual issues encountered, thus providing an informed framework for interpreting the results. Finally, several future research directions are outlined, aiming to further investigate the topic and address the identified gaps, offering both theoretical and practical insights for subsequent studies.

8.1. GENERAL CONCLUSIONS

This research aimed to explore the main **psychological, social and experiential factors** that influence the intention and behaviour of using electric and hybrid vehicles in the Italian context. Building on a solid theoretical review and the integration of technology acceptance models (e.g., UTAUT2) with user experience and environmental engagement approaches, a conceptual model was developed based on four macro-constructs: Technology Appraisal, Socio-Environmental Influence, Consumer Experience Engagement and Perceived Value.

The statistical analysis of data collected through a questionnaire administered to a sample of 364 respondents demonstrated the empirical relevance of each dimension in predicting adoption intention. The results confirm that subjective evaluations of technology (in terms of usefulness, ease of use and reliability) and the perceived user experience (both digital and practical) play a key role in shaping users' attitudes toward low-emission vehicles. At the same time, the influence of social context and personal norms related to environmental sustainability emerged strongly, helping to explain the symbolic and value-based motivations behind adoption.

The model, tested using variance analysis and regression techniques, also made it possible to identify distinct patterns among different user groups (electric, hybrid, combustion), revealing that perceptions and attitudes significantly vary depending on the type of vehicle currently used. Adoption was found to be significantly more likely among those who already experience benefits in terms of satisfaction, reliability and perceived value. In parallel, it was observed that sociodemographic factors such as age, education and residence influence the strength of relationships between variables, highlighting the need for segmented and personalised strategies in promoting sustainable mobility.

In light of the results obtained, it can be stated that the objectives outlined at the beginning of the thesis have been largely achieved. The analysis successfully identified and quantified the main factors influencing Italian consumers' intention and behaviour regarding the adoption of electric and hybrid vehicles, integrating technological, experiential, social and economic variables into a single theoretical model. The four identified proved to be significant predictors of adoption intention, confirming the validity of the proposed framework.

The hypotheses concerning the moderating effects of sociodemographic variables and the interdependencies between constructs were also supported by empirical evidence consistent with the existing literature. Furthermore, the segmentation of behaviours based on the type of vehicle used allowed for the exploration of significant differences in attitudes and perceptions, effectively addressing the fourth research question. Therefore, it can be concluded that the study successfully met its main objectives, providing a solid contribution to the understanding of Italian consumer behaviour in the context of sustainable mobility.

From a broader perspective, the results contribute to the scientific debate on how to design mobility policies and solutions that are not only technologically advanced but also psychologically acceptable, economically accessible and socially shared. The ecological transition in the automotive sector cannot be achieved without a deep understanding of consumer decision-making mechanisms, nor without an integrated approach that combines technological innovation, environmental sustainability and user experience.

Although the study has some limitations, such as the simplification of the theoretical model or the lack of clear distinction between electric and hybrid vehicles, it offers a useful framework for future investigations and for the design of marketing, policy and user-centred solutions. In conclusion, accelerating the adoption of low-emission vehicles requires a multidimensional and systemic perspective, placing at its core not only the product but also the people, values and contexts in which mobility choices are made.

8.2. STUDY LIMITATIONS

Despite the solidity of the theoretical and methodological framework adopted, this study presents some limitations that should be acknowledged with a critical perspective. These limitations concern both the **data collection phase** and **structural aspects** of the research design and provide valuable insights for improving future work on the adoption of electric and hybrid vehicles.

A first critical issue relates to the mode of **questionnaire administration**, which was conducted entirely online. While this approach made it possible to reach a large number of respondents in a short time, it may have introduced selection bias: individuals with higher digital literacy and greater sensitivity to the topic of sustainable mobility were likely more inclined to participate. This self-selection may have affected the distributions of key variables, such as technological openness or environmental concern.

Secondly, despite efforts to construct a sample as **representative** as possible of the Italian population, based on ISTAT data for age, gender and educational level, some residual discrepancies remain between the sample and the population. For example, younger individuals are slightly overrepresented, whereas older respondents are less present. Although limited, this imbalance may have influenced the aggregate estimates, especially considering that age is a significant moderator in the proposed model. Furthermore, it was not possible to ensure representativeness across all socio-demographic variables (such as income or type of residence), due both to the lack of detailed statistical availability and the need to simplify the experimental design.

A third limitation lies in the **self-reported nature** of the collected data. The measures used, though carefully developed and inspired by the scientific literature, are based on expressed perceptions and intentions, which do not always match actual behaviours. In particular, the intention to purchase or use an electric or hybrid vehicle does not guarantee actual adoption in the medium to long term. This limitation is common to many cross-sectional studies and highlights the need for future longitudinal analyses to observe potential variations over time between attitudes, intentions and real behaviours.

An additional **conceptual limitation** concerns the questionnaire design, in which many questions grouped electric and hybrid vehicles under a single category ("electric or hybrid car"). Although this choice served to keep the instrument concise and reduce cognitive load for respondents, it is important to acknowledge that substantial differences exist between electric and hybrid vehicles, both in technological terms and user experience. Electric cars imply a more radical shift for users (e.g., charging management, range, quietness, incentives), whereas hybrids often represent a compromise between innovation and continuity with prior habits. This semantic ambiguity constitutes a key area for improvement in future surveys, where evaluations related to the two types of vehicles should be systematically distinguished.

Finally, the study adopted a **simplified theoretical model**, designed to maintain a balance between analytical rigour and empirical accessibility. The decision to limit the number of variables and to aggregate multiple conceptual dimensions into macro-constructs was taken to ensure questionnaire clarity and the engagement of a generalist audience. However, this parsimony led to the exclusion of potentially relevant variables, such as the respondent's level of technical knowledge or the characteristics of their current vehicle. Although these factors are relevant in the adoption process of low-emission vehicles, they were excluded for practical and methodological reasons but deserve to be included in future research.

Despite these limitations, it is important to emphasise that the study maintains strong internal consistency, supported by statistical, theoretical and methodological validity and that it represents a significant contribution to the ongoing debate on sustainable mobility in Italy. It offers a solid foundation for empirical interventions, corporate strategies and future policymaking.

8.3. FUTURE RESEARCH DIRECTIONS

The analysis conducted in this research has provided a comprehensive and coherent overview of the factors influencing consumers' intention and behaviour toward the adoption of low-emission vehicles in Italy. However, as with any empirical investigation, this study opens the door to new questions and opportunities for further exploration. Future research directions should therefore evolve along three main axes: **theoretical model expansion**, **methodological advancement** and **contextual extension**.

A first area of development involves enriching the **theoretical model**. This thesis deliberately adopted a streamlined approach, building a conceptual framework based on four synthetic macro-variables. In the future, it would be advisable to disaggregate these constructs, investigating in greater detail the specific dimensions that compose, for instance, Consumer Experience Engagement or Socio-Environmental Influence. Additionally, variables currently excluded for model parsimony, such as users' technical knowledge, familiarity with charging infrastructure, or the influence of currently owned vehicle characteristics, could be incorporated. Recent studies suggest that factors such as technological literacy or logistical barriers can significantly shape adoption intentions.

A second evolution concerns the **expansion of methodological techniques**. On the one hand, the use of a structured questionnaire provided a solid quantitative base; on the other, integrating qualitative approaches, such as in-depth interviews or focus groups, could allow for a richer and more contextualised exploration of the underlying meanings behind certain perceptions. In this regard, mixed-methods approaches would enable the combination of statistical rigour with interpretive depth, strengthening the validity of conclusions and enhancing the understanding of motivational mechanisms.

Another possible development would involve the implementation of **longitudinal studies** to track the evolution of attitudes and adoption intentions over time, particularly in a rapidly changing technological landscape. Current public policies, economic incentives and market dynamics are swiftly reshaping the sustainable mobility landscape, making it necessary to monitor consumer behaviour from a dynamic perspective. It will be especially interesting to assess whether actual purchase behaviours converge with self-reported intentions, or whether practical barriers hinder full adoption.

Finally, extending the study to **different geographic and cultural contexts** represents an important opportunity. This research focused on the Italian population, but it would be beneficial to replicate the model in other European countries with varying levels of electric infrastructure development or distinct mobility traditions. This would allow for testing the robustness of the model and for evaluating the influence of macro-contextual variables, such as environmental policies or the average cost of electricity, on adoption behaviour.

TIME PLANNING AND BUDGETING

The **temporal planning and budgeting** of the thesis project were developed in a structured manner, with the goal of ensuring efficient management of activities and resources. The plan is divided into five main phases: initial design, development and administration of the questionnaire, data analysis, writing of the chapters and final revision [Table 20]. The overall duration of the project amounts to 142 consecutive working days (including holidays and weekends), equivalent to a total of 568 hours, based on an average of 4 working hours per day.

To estimate the total cost of the project, a simplified assumption was adopted, considering only the hourly value of the student's work, set at €30/hour. Based on this estimate, the total budget of the project amounts to **€17.040**. Costs were broken down by phase: initial design required 136 hours (€4.080), the questionnaire 76 hours (€2.280), data analysis 148 hours (€4.440), thesis writing 172 hours (€5.160) and final revision 36 hours (€1.080) [Table 21].

Task planning was guided by a **sequential logic**, with activity dependencies identified through a predecessor system. This approach made it possible to identify the **critical path** and ensure consistency between methodological phases and execution times. The entire work took place between **1st February 2025 and 22nd June 2025**, in line with academic deadlines and with a balanced distribution of the workload [Figure 24]. The integrated view of time and cost provided a useful tool for **self-assessment and progress monitoring** throughout the project.

Table 20: Thesis project timeline: Phases, tasks, durations and dependencies. Source: Author's elaboration.

ID	Phase / Task	Duration (days)	Start date	End date	Predecessors
	1. Initial design and setup	**34**	**01/02/2025**	**06/03/2025**	
1.1	Definition of topic and objectives	2	01/02/2025	02/02/2025	-
1.2	Literature review	14	03/02/2025	16/02/2025	1.1
1.3	Definition of thesis structure	4	17/02/2025	20/02/2025	1.2
1.4	Discussions with supervisors (periodic meetings)	7	21/02/2025	27/02/2025	1.3
1.5	Definition of theoretical model and variables	7	28/02/2025	06/03/2025	1.4
	2. Questionnaire development and administration	**19**	**07/03/2025**	**25/03/2025**	
2.1	Questionnaire development and validation	9	07/03/2025	15/03/2025	1.5
2.2	Survey administration and data collection	10	16/03/2025	25/03/2025	2.1
	3. Data analysis	**37**	**26/03/2025**	**01/05/2025**	
3.1	Dataset cleaning and checking	5	26/03/2025	30/03/2025	2.2
3.2	Descriptive and inferential analysis (Shapiro, ANOVA...)	14	31/03/2025	13/04/2025	3.1
3.3	Advanced analysis (SEM, regressions, etc.)	14	14/04/2025	27/04/2025	3.2

3.4	Creation of tables and graphs	4	28/04/2025	01/05/2025	3.3
4. Thesis writing		**43**	**02/05/2025**	**13/06/2025**	
4.1	Chapter 3 – Theoretical framework	7	02/05/2025	08/05/2025	1.4
4.2	Chapter 4 – Application to the automotive sector	7	09/05/2025	15/05/2025	4.1
4.3	Chapter 5 – Model and methodology	7	16/05/2025	22/05/2025	2.1, 4.2
4.4	Chapter 6 – Data analysis	10	23/05/2025	01/06/2025	3.4, 4.3
4.5	Chapter 7 – Discussion and implications	6	02/06/2025	07/06/2025	4.4
4.6	Introduction, abstract, references, appendices and other elements	6	08/06/2025	13/06/2025	4.5
5. Final review and submission		**9**	**14/06/2025**	**22/06/2025**	
5.1	Revision with supervisors	2	14/06/2025	15/06/2025	4.6
5.2	Proofreading + APA formatting + final review	3	16/06/2025	18/06/2025	5.1
5.3	Submission + preparation for thesis defense	4	19/06/2025	22/06/2025	5.2

Table 21: Time planning and estimated cost of the thesis project. Source: Author's elaboration.

Phase	Duration (days)	Duration (hours)	Cost (€)
1. Initial design and setup	34	136	4.080 €
2. Questionnaire development and administration	19	76	2.280 €
3. Data analysis	37	148	4.440 €
4. Thesis writing	43	172	5.160 €
5. Final review and submission	9	36	1.080 €
Total	**142**	**568**	**17.040 €**

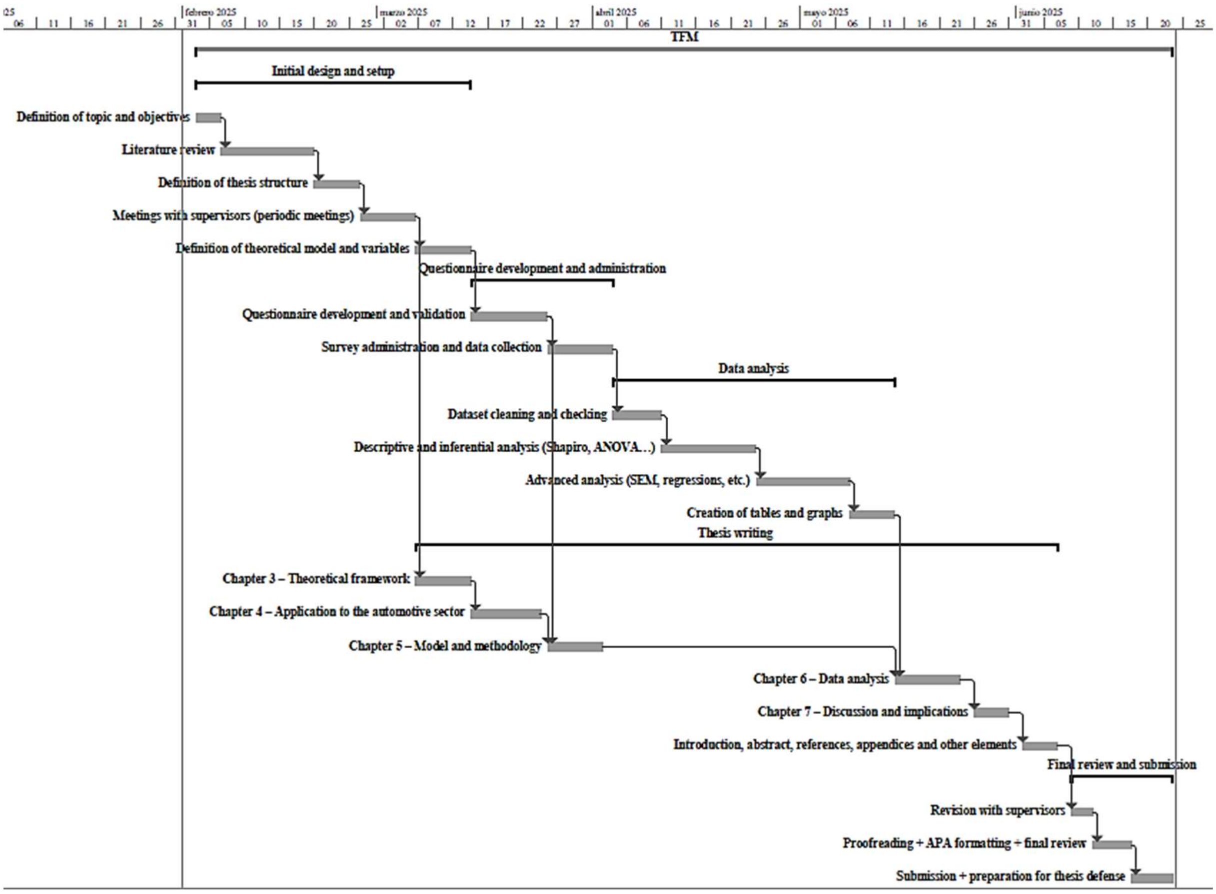

Figure 24: Gantt chart of the thesis project timeline. Source: Author's elaboration.

EVALUATION OF IMPACTS: SOCIAL, ECONOMIC, ENVIRONMENTAL AND OTHER RELEVANT ASPECTS

Widespread adoption of low-emission vehicles entails a series of significant impacts that extend beyond the individual level, reaching society, the economy and the environment. From a social perspective, promoting the transition to sustainable mobility implies **ensuring equitable access** to new technologies, reducing inequalities linked to the availability of infrastructure (e.g., charging stations) and fostering a cultural shift in consumption models. The **economic dimension** is equally crucial: while the adoption of electric vehicles can generate long-term savings and stimulate industrial innovation, there remains a risk of **exclusion** for lower-income social groups due to still high upfront costs.

The **environmental impact** is the primary motivation driving the ecological transition. The spread of electric and hybrid vehicles can significantly reduce CO_2 emissions, urban air pollution and dependency on fossil fuels. However, it is also necessary to consider indirect impacts stemming from battery production, the national energy mix and the vehicle life cycle. Finally, there is an important **ethical and professional dimension**: technological choices and incentive policies must be accompanied by **transparent, sustainable and evidence-based decision-making** processes, to ensure that the tools implemented are genuinely effective in driving change without generating distortive or counterproductive effects.

ANALYSIS OF LEGAL AND ETHICAL ASPECTS

The technological evolution in the automotive sector, particularly the spread of electric and hybrid vehicles, raises a number of important **legal and ethical issues** that must be carefully considered both in public policy design and in the management of research activities. From a legal standpoint, the introduction of new mobility technologies requires **continuous regulatory updates**, aimed at governing aspects such as safety, liability in the event of accidents, consumer protection and the safeguarding of data generated by connected vehicles. In this context, European legislation plays a key role, setting increasingly stringent environmental standards and promoting sustainable practices through specific directives and regulations (such as EU Regulation 2019/631 on CO_2 emissions from new passenger cars).

On the ethical side, the research conducted followed the principles of **responsibility, transparency and respect for participants**. The questionnaire was structured to ensure anonymity, data confidentiality and exclusive use for scientific purposes. In line with the **GDPR**, no sensitive data were collected and every participant could freely choose whether or not to take part. More broadly, promoting electric mobility entails a **broader ethical commitment** to environmental sustainability, inclusivity and intergenerational justice: adopting low-emission technologies is not only a functional choice, but an **act of collective responsibility** toward the future of the planet and upcoming generations.

CONTRIBUTION TO THE SUSTAINABLE DEVELOPMENT GOALS (SDGS)

The research work carried out in this thesis is fully aligned with the **United Nations 2030 Agenda**, offering a concrete contribution to several **Sustainable Development Goals (SDGs)**, particularly **Goal 11** (sustainable cities and communities), **Goal 12** (responsible consumption and production) and **Goal 13** (climate action). By analysing the factors that influence the adoption of low-emission vehicles, this thesis promotes a critical reflection on consumer behaviour and on the role of public policies in driving the transition toward more sustainable mobility.

Moreover, the theoretical model proposed and the empirical investigation conducted aim to identify effective levers to increase environmental awareness, encourage responsible choices and support the development of infrastructure and services that make the use of electric and hybrid vehicles more accessible. This approach also links to **Goal 9** (industry, innovation and infrastructure), by fostering the adoption of sustainable technological solutions in key sectors such as automotive and urban logistics. Finally, by focusing on ethical, social and equity aspects in access to sustainable mobility, the thesis also contributes to **Goal 10** (reduced inequalities), supporting a more inclusive approach to the ecological transition.

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ANNEX 1: Q-Q PLOTS AND RESIDUALS VS FITTED VALUES GRAPHS

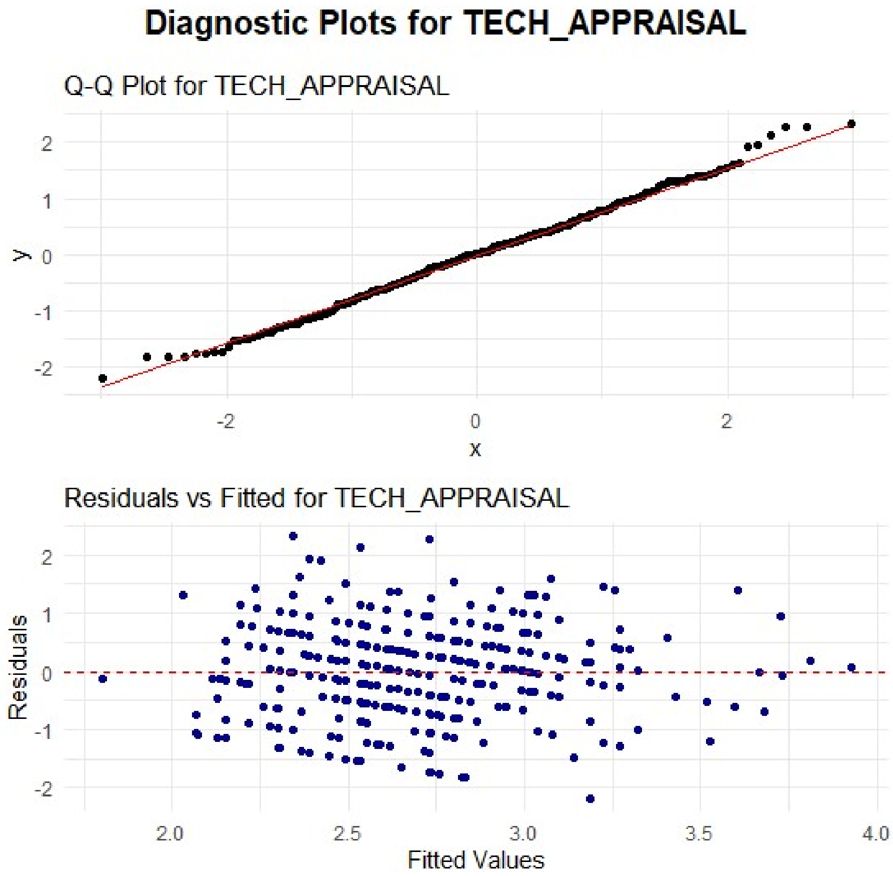

Figure 25: Diagnostic plots for Technology Appraisal – ANOVA residuals. Source: Author's elaboration.

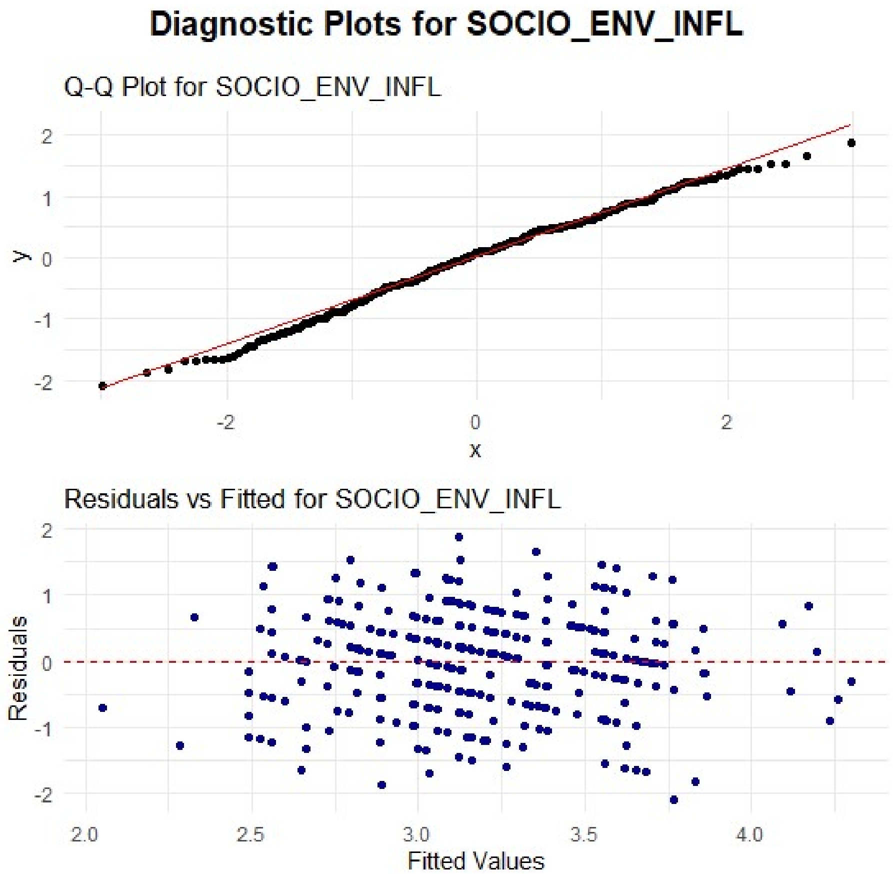

Figure 26: Diagnostic plots for Socio-Environmental Influence – ANOVA residuals. Source: Author's elaboration.

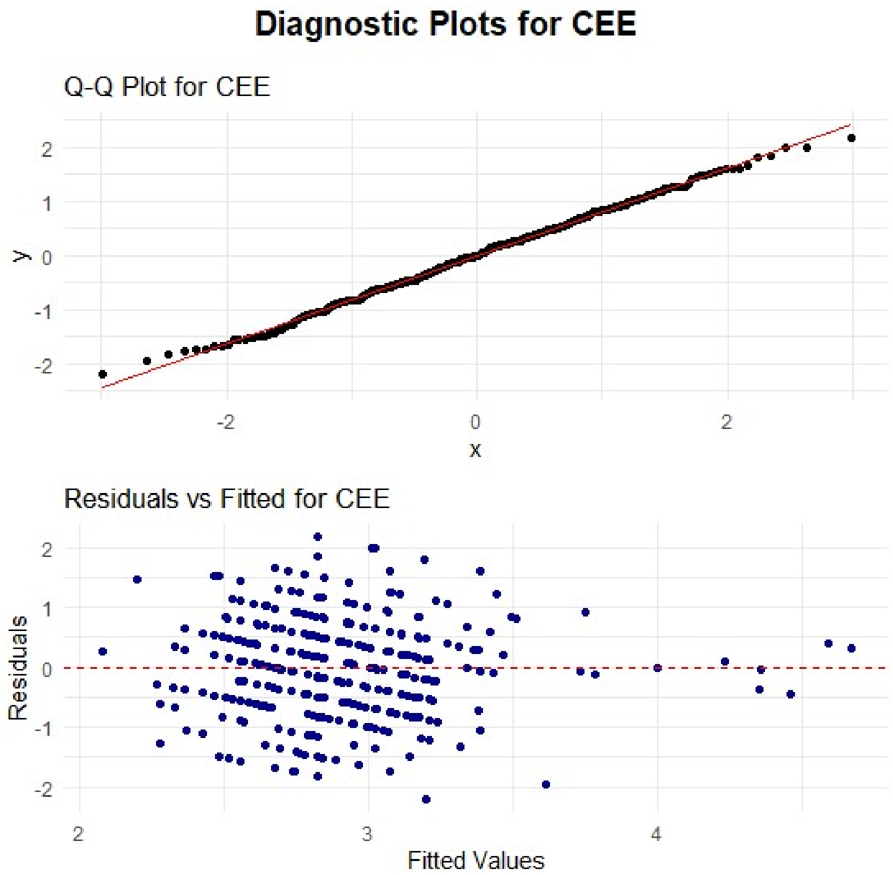

Figure 27: Diagnostic plots for Consumer Experience Engagement – ANOVA residuals. Source: Author's elaboration.

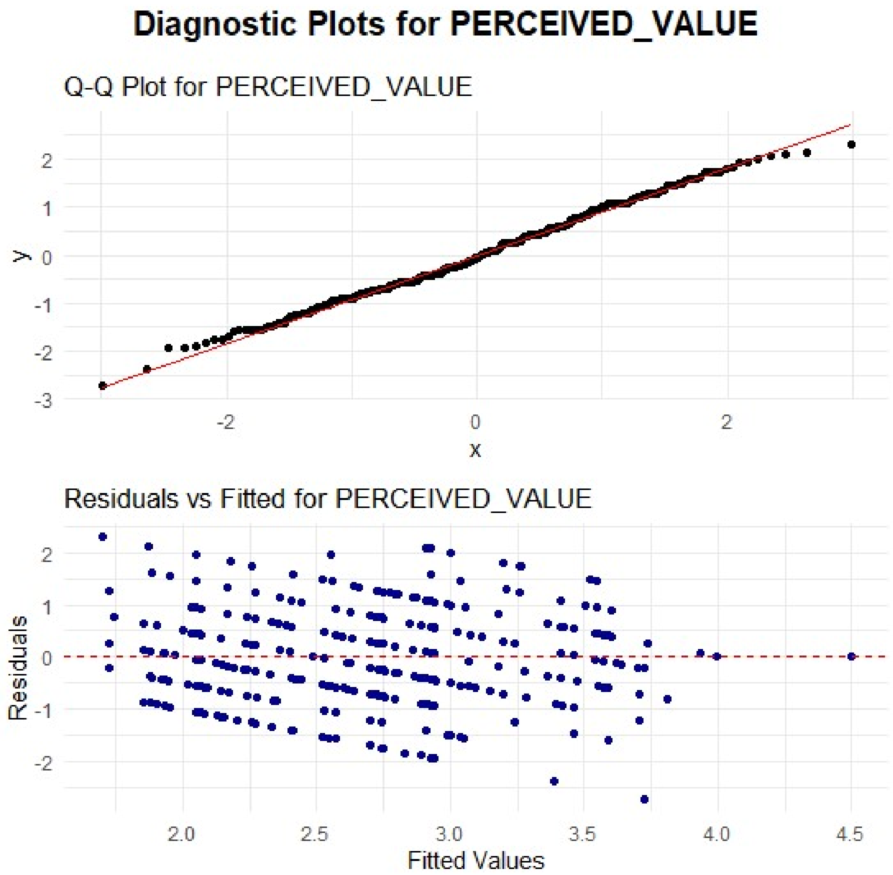

Figure 28: Diagnostic plots for Perceived Value – ANOVA residuals. Source: Author's elaboration.

ANNEX 2: QUESTIONNAIRE

1. Do you have a driver's license and regularly drive a car?
   - ☐ Yes
   - ☐ No (if "No", end the questionnaire)
2. Age: ____ years.
3. Gender:
   - ☐ Male
   - ☐ Female
   - ☐ Other / Prefer not to say
4. Highest level of education:
   - ☐ Compulsory education
   - ☐ High school diploma
   - ☐ University degree
   - ☐ Other
5. Type of residence:
   - ☐ Urban
   - ☐ Suburban
   - ☐ Rural
6. Monthly net household income:
   - ☐ Less than €2,000
   - ☐ €2,000 – €2,999
   - ☐ €3,000 – €3,999
   - ☐ More than €4,000
7. Years of driving experience: ____ years.
8. What type of car do you currently use most frequently?
   - ☐ Internal combustion vehicle (gasoline/diesel)
   - ☐ Hybrid vehicle
   - ☐ Electric vehicle
9. Have you ever driven a hybrid or electric car, even if not owned by you?
   - ☐ Yes
   - ☐ No

Please indicate your level of agreement with the following statements *(responses on a 1–5 Likert scale:* 1 = Strongly disagree; 2 = Somewhat disagree; 3 = Neither agree nor disagree; 4 = Somewhat agree; 5 = Strongly agree)

10. I believe that driving a hybrid or electric vehicle would improve my travel efficiency compared to a combustion vehicle.

11. Managing the charging and maintenance of a hybrid/electric vehicle would be easier than for a combustion vehicle.
12. I believe hybrid/electric vehicles are safer and more reliable than combustion vehicles.
13. My friends, family, or colleagues would approve of choosing a hybrid or electric vehicle over a combustion vehicle.
14. My friends, family, or colleagues would positively influence my decision to purchase a hybrid/electric vehicle.
15. I feel morally obliged to choose mobility solutions that reduce environmental impact.
16. There is adequate infrastructure (e.g., charging stations) in my area for using an electric vehicle.
17. I believe it would be easy to get technical support for a hybrid/electric vehicle in my area.
18. Driving a hybrid/electric vehicle would be a more enjoyable experience than driving a combustion vehicle.
19. I have found, or would find, it difficult to switch from driving a combustion vehicle to a hybrid or electric one.
20. I think the benefits of a hybrid or electric vehicle justify its higher price compared to a combustion vehicle.
21. I consider investing in a hybrid/electric vehicle more economically advantageous in the long term than a combustion vehicle.
22. If I were to buy a new car, I would probably choose an electric or hybrid model.