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Exploring consumer adoption of zero-emission vehicles: Integrating behavioural reasoning and construal level theory in early technology diffusion

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HIGHLIGHTS

- Integrates BRT and CLT to explore consumer behavior in emerging green markets.
- Proposes a BRT model extension including familiarity in sustainability contexts.
- Examines cognitive shifts in consumer evaluations of green technologies.
- Employs experimental design to assess products at different market diffusion stages.
- Offers practical insights for firms promoting sustainable technologies and strategies.

ABSTRACT

The environmental crisis has made the development and diffusion of green products a critical challenge, compelling companies to adopt eco-innovator roles and align with consumer preferences for sustainable solutions. However, limited attention has been paid to understanding the evolution of consumer cognitive processes when evaluating solutions that are not yet market-ready. Drawing on Behavioural Reasoning Theory (BRT), this paper integrates insights from the Construal Level Theory to explain how cognitive mechanisms shape consumers' attitudes towards zero-emission vehicles.

Specifically, the study examines how these mechanisms change when consumers evaluate existing products, prospective products, or the broader product category, by introducing targeted manipulations to test a BRT model extended with familiarity as an attitudinal antecedent. The research uses a between-group experimental design in which 1071 Italian consumers were randomly assigned to a specific evaluative condition. The findings show that familiarity negatively relates to reasons against, and values positively influence reasons for and attitudes. Both relationships are valid regardless of manipulation. Instead, familiarity positively impacts reasons for, and values negatively affect reasons against, varying with product diffusion stages and abstraction levels. This study enriches green technology adoption literature by advancing BRT, emphasising the role of familiarity and psychological distance in impacting consumer cognition. Managerial implications underscore the need for an iterative product development process, driven by continuous customer analysis to capture shifts in perceptions and preferences across diffusion stages. They also stress the importance of tailored communication strategies, balancing value-driven and feature-based messaging to trigger relevant cognitive drivers at each adoption stage.

1. Introduction

The imperative to reduce the environmental impact of production and consumption processes drives businesses to rethink their processes and products to align with the demands of the so-called "ecological transition" (Guyader et al., 2022). As a result, companies are increasingly expected to embrace the role of eco-innovators, addressing consumer preferences and needs, a dual challenge that is particularly complex in industries with relevant path dependencies, such as automotive (McMeekin and Southerton, 2012; Rizzi et al., 2014). The industrial dynamics at the regional level in the EU are reducing the resources available for investment (Zsolt, 2023), exacerbating dilemmas

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concerning how to invert the decline in sales and help consumers navigate alternative offerings (Ziegler and Abdelkafi, 2023) in fluctuating market conditions (Calabrese and Tang, 2023; Du et al., 2024). It is thus crucial for firms to understand how consumers process promotional cues in such a complex environment (Saeed et al., 2020).

High-involvement products, such as cars (Nayeem and Casidy, 2013), further complicate the decision-making process, as consumers are required to exert greater cognitive effort due to the substantial volume of information that must be processed (Lou and Xie, 2021). The extended process that individuals undertake prompts them to thoroughly consider the various positive and negative factors of alternatives (Nayeem and Casidy, 2013). For this reason, among the theories addressing consumer behaviour, the Behavioural Reasoning Theory (BRT) appears to be well-suited to serve as a theoretical framework for high-involvement purchasing products. BRT has recently gained attention for its ability to disentangle how individuals use reasons for and reasons against to justify and defend their actions, thereby shaping their overarching motives and intentions (Westaby, 2005). By deconstructing the reasons for and against individuals' target behaviour, BRT has the potential to capture the multifaceted dimensions shaping consumer cognition when processing stimuli related to both dominant and emerging products (Huang and Qian, 2021).

However, in the latter case, despite initial evidence of BRT's application also in the automotive sector (Uddin et al., 2024; Sahu et al., 2020), autonomous vehicles (Qian et al., 2023), electric vehicles adoption and sharing (Claudy et al., 2015; Chen et al., 2021; Eccarius et al., 2023), its potential to inform marketing strategies for emerging product categories characterised by products with different stages of diffusion remains largely unexplored. In particular, it is necessary to investigate the differences that may arise when consumers evaluate a *product category*, which is generic and lacks technological specificity, a *prospective product*, which is a technological reality that has yet to establish itself in the market, or finally, an *existing product*, which is currently available and undergoing market diffusion. This objective concerns the understanding of consumers' cognitive processes about new, high-involvement, and psychologically distant products in significant real-life settings. This is particularly salient in the context of zero-emission vehicles considered as an entire product category or battery electric vehicles (BEV) and fuel cell vehicles (FCEV), representing existing and prospective products characterised by technologies at a specific stage of diffusion.

In this regard, the intersection between BRT and Construal Level Theory (CLT) can provide valuable empirical evidence (Saeed et al., 2024). In fact, from this perspective, CLT can usefully complement BRT when interpreting differences in how consumers value the "reasons for" and "against" concerning products that, being at early adoption stages, are not yet fully tangible. Furthermore, CLT also provides the rationale for assuming that the mental representations and the related cognition of "reasons for" and "against" vary with the perceived familiarity with the object of the evaluation (Förster, 2009). Given the potential for conceptual integration, exploring the intersection of BRT and CLT can reasonably enhance our understanding of how firms can cultivate consumers' interest in learning about their innovative products, which is, from a logical standpoint, an important precursor to their eventual adoption.

To start filling this gap, the following section reviews BRT, drawing elements from the CLT to frame how familiarity can complement the BRT conceptual model to explain how values, familiarity, reasons for and against shape the consumer cognitive process to learn about BEV and FCEV, two types of innovative zero-emission vehicles that differ significantly in terms of market diffusion, or zero-emission vehicles as a whole (i.e., product category), which is typical for companies competing for the market and not only in the market.

In the methods section, we describe the experimental design employed to collect empirical evidence on how consumers elaborate typical and comparable stimuli concerning BEV (existing product), FCEV (prospective product), and the product category of zero-emission vehicles. The results and discussion section examines the hypothesised relationships and provides critical insights that inform the discussion. At the same time, theoretical predictions are enriched with empirical evidence, providing insights into the differences among the product category, prospective product and existing product. In the concluding section, this integration leads to the development of actionable recommendations for marketers aiming to promote their products effectively and, most of all, understand how to tailor marketing strategies to targeted audiences based on the product's unique characteristics or its overall category.

2. Review of literature and hypotheses development

2.1. The Behavioural Reasoning Theory and the proposed model

The BRT (Westaby, 2005; Claudy et al., 2015) framework underpins the theoretical foundation of this study. BRT is a recent approach that has rapidly gained traction in the literature on behaviours that explains technology adoption. The primary advantage of this theory is its ability to propose a model that considers both enabling and inhibiting factors for adopting new technology (Jan et al., 2023). Integrating both aspects is particularly relevant considering that the "reasons against" (RA) are not merely the "reasons for" (RF) that act in the inverse directions and, thus, in many cases, constitute different constructs (Claudy et al., 2015).

Despite its recent theorisation, the BRT has proven versatile and applicable to the fields considered in this study, such as high-involvement products (Claudy et al., 2013, 2015), the adoption of pro-environmental behaviours (Dhir et al., 2021), and the mobility sector (Uddin et al., 2024; Chen et al., 2021; Qian et al., 2023). BRT is particularly suitable for highly complex decision-making situations (Peterson and Simkins, 2019) as it focuses on how consumers elaborate reasons to reduce cognitive dissonance (Westaby et al., 2010).

Claudy et al. (2015) theorise a model in which values are precursors of RF/RA, which influences the attitude towards adoption. Attitude, in turn, shapes the intention to adopt, which is directly connected to the adoption behaviour. These final relationships of the model (between attitude and intention and between intention and behaviour) stem from more widespread theories, such as the well-established Theory of Planned Behaviour (TPB) (Ajzen, 1991) and thus do not require additional empirical support.

The proposed model is an adaptation of the original model. This includes the structural variables of the model (i.e., Values, RF, RA, Attitude), as implemented in Claudy et al. (2013, 2015), as well as additional variables introduced in this study to enhance the framework (i.e., Familiarity). This extension was developed based on insights derived from Construal Level Theory (Liberman and Trope, 1998). Hence, the present study intends to provide some first insights into the ability of CLT to enrich the decision-making process shown in the BRT approach, supporting the idea that an individual's perceived psychological distance influences the formation of the key variables in this theory (particularly the reasons) (Liberman and Trope, 1998).

As in the original BRT model, our model considers values as an antecedent. A value is "*a belief pertaining to desirable end states or modes of conduct that transcends specific situations, guides selection or evaluation of behaviour, people, and events, and is ordered by importance relative to other values to form a system of value priorities*" (Schwartz, 1994, p. 20). In line with theoretical models that adopt psychographic variables to predict consumer behaviour, such as the Value-Belief-Norm Theory (VBN, Stern et al., 1999), values are direct or indirect antecedents of attitude, intention, and behaviour in green settings (Groening et al., 2018). Although BRT studies operationalise values in many different ways, in green settings values are typically framed as "environmental values" (see, for example, Zhu et al., 2023; Sreen et al., 2023), which are individual or collective beliefs on the importance and the role of the natural environment and how human being can interact with it (Reser and

Bentrupperbäumer, 2005).

In the BRT model theorised by Claudy et al. (2015), values are the sole antecedents of the "reasons". Integrating the CLT, this theoretical approach provides insights into dimensions that could enhance BRT to improve further its ability to explain intentions. In fact, CLT points to familiarity, which is the opposite of the lack of experience. Familiarity is a common trait of the various types of psychological distance (Liberman and Förster, 2008), representing an important factor that influences the construal level of an event or product (Förster, 2009). Familiarity can be considered a stratification of past experiences and information (Alba and Hutchinson, 1987; Rao and Sieben, 1992). Growing consumers' confidence in a product or product category modifies their decision-making process primarily by altering the relationships with behavioural antecedents, such as trust, satisfaction, and loyalty (Fandos Herrera and Flavián Blanco, 2011). Similarly, Rizzi et al. (2020) found that exposure to information positively influences the behavioural antecedents in TPB. The mechanism by which familiarity influences decision-making suggests that it affects the learning process through the quantity and type of new information gathered and processed (Johnson and Russo, 1984). Fischer and Frewer (2009) demonstrated that even the relationship between risk and benefit perception varies according to the level of familiarity due to the activation of risk perception and heuristics. These results suggest that familiarity can usefully extend the BRT model, given its influence on RF/RA. No extant study has tested the possibility of expanding the BRT with the familiarity variable, understood as an antecedent of equal standing to values. This represents one of the innovative contributions of this paper, allowing us to fill a gap in the current BRT-based literature.

In the proposed model, both values and familiarity are considered predictive variables of the RF/RA. These are the innovative and crucial variables of the original BRT model. Westaby (2005) introduces the concept of "reasons" in a behavioural intention model, arguing that it serves as a "bridge" between the most intimate characteristics of an individual (beliefs and values) and the global motives (attitude, subjective norms, and perceived control). Also, Claudy et al. (2015) give "reasons" for the core role of strong motivational forces that can act positively or negatively in favour or against a specific behavioural intention, further underlying the difference between beliefs and reasons. Beliefs are broadly construed and refer to general thoughts, while reasons are narrow visions of the behaviour considered (Westaby, 2005). Relating to innovation adoption, "*beliefs would thus reflect people's opinion about the innovation characteristics in general, whereas reasons for/against adoption would constitute specific factors that influence the purchase decision*" (Claudy et al., 2015, p. 533).

Finally, as in the original model, our model tests the relationship between "reasons" and attitude, which is considered one of the global motives (Westaby, 2005), highlighting its ability to predict intention in different behavioural settings and contexts. It is generally considered a positive or negative evaluation of specific behaviour (Ajzen, 2001). Attitude is one of the most frequently adopted variables in behavioural models. Bagozzi and Kimmel (1995), comparing the leading theories for predicting behaviours (such as the Theory of Reasoned Action, the TPB, and the Theory of Self-regulation), found that attitude significantly explains the intention in all the considered models.

Increasingly, studies employ BRT to identify context-specific reasons that explain factors favouring or hindering certain behaviours. This is demonstrated by recent applications of the BRT in specific sectors (Uddin et al., 2024; Mohanty et al., 2025), which also serve to confirm or disconfirm the relationships among the original variables of the model (Panda and Ramalingam, 2024).

In addition to suggesting operational factors for encouraging zero-emission vehicle use, this study has two primary objectives. These objectives are to understand if and how familiarity acts as an antecedent to reasons, and how the decision-making process is structured and varies when moving from considering a product category to a product. Furthermore, in this latter case, it examines the shift from a product already widespread in the market to one in its early stages of diffusion. The paper, therefore, seeks to fill these two gaps in the literature, which are interesting not only for a better understanding of how consumers decide, but also for providing more precise indications based on what the consumer is evaluating.

The proposed model is shown in Fig. 1.

2.2. The hypotheses development

Most of the literature operationalising BRT primarily focuses on verifying the positive/negative influence RF and RA have on attitude. While these linkages are well-established in the extant literature, investigations comparing the effects and magnitude of RF and RA on attitude remain absent.

Claudy et al. (2015), in their theoretical discussion of the differences between RF and RA, pointed out how the "loss aversion" effect can lead consumers to overestimate barriers compared to advantages (Kahneman and Tversky, 1979). This means consumers could perceive the losses resulting from adopting innovations more heavily in absolute terms than the benefits (Claudy et al., 2015). Nevertheless, empirical data do not always support this reasoning, as recent studies suggest that RF may have a higher absolute effect on attitude than RA (Uddin et al., 2024; Yadav et al., 2022; Jan et al., 2023; Qian et al., 2023). This can be explained by considering that, in these studies, consumers are asked to evaluate a hypothetical future purchase, attitude, or intention to buy or adopt a product or innovation, leading respondents to perceive a high psychological distance, which, according to the CLT (Liberman and Trope, 1998), can be determined by spatial, social, and hypothetical distance. The temporal distance from a hypothetical purchase is a factor that can change an individual's perception and influence mental construal (Liberman et al., 2002). An object or event is mentally represented as concrete or low-level construal when it is temporally close, whereas it is considered abstract or high-level construal when it is temporally distant (Liberman et al., 2002). In such circumstances, the pros are overestimated and outweigh the cons (Trope et al., 2007) as individuals get more confident when thinking about something temporally distant than something temporally close, making it easier to generate pros versus cons when referring to future events cognitively (Herzog et al., 2007). This overestimation may be particularly relevant within decision-making processes concerning high-involvement products, regardless of whether they are a product category, a prospective product, or an existing one, which require significant consideration and effort. Then, our first hypothesis is the following.

H1. RA have a universally lower impact on attitude compared to RF in high-involvement products

The effect of loss aversion (Kahneman and Tversky, 1979) is crucial to analysing how RA take shape in individuals' minds and influences

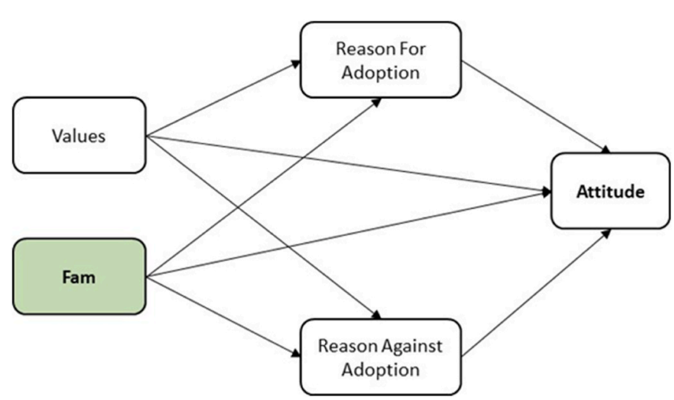

Fig. 1. The proposed model adapted from Westaby (2005) and Claudy et al. (2015).

decision-making. Beyond the fact that loss aversion also depends on consumer characteristics, it is stronger in the case of durable (Neumann and Böckenholt, 2014) and expensive products (Mukherjee et al., 2017), such as high-involvement products.

Studies examining the strategies consumers use to address loss aversion often find information seeking as key to reducing the uncertainty deriving from loss aversion and risk perception (Sheth and Venkatesan, 1968). The same can be argued for brand loyalty (Roselius, 1971), which assumes that the product has been purchased in the past and can, therefore, benefit from the specific experience gained. As Yeung et al. (2010) confirm the significant role of brand and information in addressing perceived risk, and since familiarity itself develops from information and experience (Alba and Hutchinson, 1987; Rao and Sieben, 1992), it follows that familiarity can lessen risks and loss aversion, a point reinforced by recent research (Xu and Zeng, 2022). This cognitive mechanism can be considered overarching, and its validity is universal across product category, and prospective and existing products. Then, we hypothesise the following.

H2a. Familiarity is negatively and universally related to RA in high-involvement products

RF assist individuals in making sense of their world by offering causal explanations for their behaviour (Westaby, 2005). This is because individuals feel better about their choices when they have justifiable and well-structured reasons to support their behaviour (Pieters and Zeelenberg, 2005), especially in the case of green products, which are linked to value-driven attributes (Khan and Mohsin, 2017; Ng et al., 2024). Previous research has highlighted that the formation of RF is closely tied to individuals' beliefs (Claudy et al., 2013) and their deep compatibility with personal values (e.g., Garcia et al., 2007; Karahanna et al., 2006; Kleijnen et al., 2009). Therefore, RF takes shape in individuals' minds both by searching for practical confirmation to justify and defend their behaviour (Pieters and Zeelenberg, 2005) and by seeking alignment with personal values and reinforcement of self-esteem (Kunda, 1990; Steele et al., 1993). This reinforcement can occur through the knowledge and experience accumulated by individuals at a superordinate level, that is, familiarity, emphasising the benefits of a particular choice. Westaby (2005, p. 102) states that "*individuals first collect information about decision alternatives and then evaluate the credibility and value of the information when generating their reasons*."

However, this backwards-looking process aimed at constructing and validating RF may not hold when the evaluation shifts from the product category to an existing or prospective product (Laroche et al., 2010). The product category is more difficult to evaluate than (existing or prospective) product (Laroche et al., 2010) due to its greater vagueness and generality of characteristics. By contrast, evaluations of existing or prospective products tend to rely on more technical and concrete information, which may conflict with the value-driven reasoning that typically informs RF. Therefore, familiarity does not necessarily result in an optimistic perception of the product's positive attributes, especially in the green setting, where green product categories are often desired regardless of the confidence in their existing and prospective products, leading to differences in how familiarity elicits a more sceptical attitude. We thus hypothesise the following.

H2b. For high-involvement products, familiarity is positively related to RF only for the product category

Values are among the most recurrent and effective antecedents in the main theoretical models explaining consumer behaviour. Westaby (2005) and Claudy et al. (2015) postulated that values are precursors of RF and RA. In particular, Claudy et al. (2015) find that values positively influence RF and do not influence RA. In the most recent applications of the BRT, the role of values in the applied conceptual models is heterogeneous, and the results are discordant. Sometimes, they are used to classify respondents (Kumar et al., 2023).

Considering only the cases in which environmental values are at focus, Dhir et al. (2021) found that values do not influence RF but have a negative relation with RA, while Sreen et al. (2023) and Chatterjee et al. (2022) found a positive link with both RF and RA. Among the explanations of these dissimilarities, the CLT (Liberman and Trope, 1998) complements product-specific considerations by suggesting that individuals questioned about future events cognitively tend to represent them abstractly due to the perceived temporal distance (Liberman et al., 2002). In the case of temporal distance, "*pragmatic concerns are subordinate to people's inner, idealistic values*" (Trope et al., 2007, p. 90). Then, in evaluating a temporally distant event, individuals tend to favour an idealistic vision, which might be particularly influential in the case of a value-related product, leading to more optimistic evaluations (Trope et al., 2007). In the case of high-involvement products, values are thus expected to emphasise RF. Then, our hypothesis is stated as follows.

H3a. Values are positively and universally related to RF in high-involvement products

If values emphasise the pros when an idealistic self-representation is activated (Kivetz and Tyler, 2007), we can conversely hypothesise that they could also mitigate, at least to some extent, the effect of the cons. In this second case, it is essential to distinguish how the tendency of consumers to idealise a product category varies compared to an existing or prospective product because of the differences in the related shortcomings they recall. Since the formation of RA involves factors such as uncertainty and loss aversion, which intensify perceived risk and, consequently, can amplify the evaluation of cons (Kahneman and Tversky, 1979; Sheth and Venkatesan, 1968), it is essential to understand the type of risk that comes into play during the evaluation to unravel its effect on RA formation. Aligning with Bettman's (1973) classification of risks, we differentiate between "inherent risk", associated with the product class, and "handled risk," which pertains to the existing and prospective products. From this perspective, when referring to green products, since the category is harder to delineate precisely and the related information seeking is harder to pursue compared to existing and prospective products (Laroche et al., 2010), an idealistic vision may prevail, which allows values to reduce the RA (Trope et al., 2007). On the contrary, the evaluation of existing or prospective products can benefit from the availability of recalling prior experiences and specific knowledge directly related to the product. This may lead to a more pragmatic view and a focus on concretely delineated risks that may decrease the significance of the idealistic perspective. Consequently, the values may not be able to mitigate the specific and well-defined concerns related to a particular technology. This reasoning justifies our following hypothesis.

H3b. For high-involvement products, values are negatively related to RA only for the product category

Several studies have demonstrated attitude to be a key predictor of pro-environmental behaviour, such as electric vehicle adoption (Jansson et al., 2011), renewable energy installation (Bruner and Kumar, 2007; Claudy et al., 2015; Dabholkar and Bagozzi, 2002) and recycling practices (Chung and Leung, 2007). BRT posits that attitude mediates the effect of reasons and values in predicting the final behavioural intention. In this regard, familiarity – stemming from knowledge, information, and past experiences – plays a significant role in the cognitive processes that shape behaviour through attitudes. Indeed, scholars have found that exposure to general information and increased familiarity with a product can reshape consumers' informational foundations, thereby serving as a background variable influencing attitude (Witzling et al., 2015; Trumbo and O'Keefe, 2001).

Although behavioural studies provide a solid theoretical foundation on the role of familiarity in predicting attitude, to date, empirical evidence is still needed to demonstrate familiarity's ability to enhance BRT and improve the explanatory power of its behavioural model. To this end, we hypothesise that familiarity directly affects attitudes towards product category, and prospective or existing products, independent of complete mediation through reasons. Our hypothesis is stated as follows.

H4. Familiarity is positively and universally related to attitude in high-involvement products

Values are expected to directly affect attitudes towards product category, and existing and prospective products, without full mediation through reasons (Westaby, 2005). In fact, in line with our previous hypothesis, the cognitive justifications individuals use are influenced not only by situational deliberate reasoning but also by automatic value-driven elaborations that can circumvent deeper levels of rational thought activation (Bargh et al., 1996; Fazio et al., 1995; Mitchell and Beach, 1990).

When dealing with green products, environmental values reflect the collective beliefs on the importance and the role of the natural environment (Wensing et al., 2019; Zhu et al., 2023; Sreen et al., 2023). Several findings support the assumption that environmental values predict environmental attitudes that lead to green consumer behaviour (Schultz and Zelezny, 1999; Schwartz, 1992; Schwartz and Bilsky, 1990).

However, previous studies (Groening et al., 2018) have shown that environmental values do not always translate into green consumer behaviour, highlighting the importance of exploring scenarios where environmental values do not seamlessly translate into green action. Building on this potential disconnect between idealistic intentions and pragmatic actions, we recognise the need to deepen the understanding of the relationship between environmental values and attitude. Specifically, we seek to investigate whether values consistently act as predictors of attitudes, regardless of product specificity (existing or prospective products) or the higher-level category to which the product belongs (product category).

For this reason, we test the effect of values on attitude with the following hypothesis.

H5. Values are positively and universally related to attitude in high-involvement products

3. Methods

3.1. Research setting

Testing the hypotheses outlined above requires a research setting focused on high-involvement products, aligning well with the characteristics of the automotive sector in countries adopting vehicles for ecological transition. In this regard, the European electric vehicles market has experienced steady growth over the past five years, with a significant rise in the number of registered BEV and Plug-in Hybrid Electric Vehicles (PHEV), in line with global trends (IEA, 2024; EEA, 2024). Despite the overall growth across Europe, there are marked disparities in electric vehicle registrations among the major regional economies.

Among the countries with a lower adoption rate of zero-emission vehicles, in 2022, Italy registered approximately 115,000 EVs, accounting for less than 9 % of total registrations, significantly below the European average (OECD, 2024). Italy has a deeply ingrained traditional automotive industry, primarily represented by the holding Stellantis (which includes the Italian brands Fiat, Alfa Romeo, Lancia, and Maserati), which covers 17 % share of the European market and makes it the second-largest vehicle seller after the German Volkswagen Group in terms of total vehicles sold (Stellantis, 2024).

From a regulatory and policy perspective, Italy has demonstrated a clear commitment to promoting industrial policies aimed at facilitating the energy transition. As outlined in the National Energy and Climate Plan (PNIEC), Italy's strategic document for energy and climate policy, there is a commitment to reach 20 % zero-emission vehicles by 2030, equating to approximately 6.6 million fully electric cars (MASE, 2023).

These targets are highly ambitious, considering the current rate of electric vehicle registrations (BEV + PHEV). Without a substantial acceleration toward sustainable mobility, the current penetration of zero-emission vehicles will not even approach half of the projected 3.8 million electric vehicles outlined in the PNIEC.

This context, characterised by the absence of significant structural barriers, provides a particularly promising opportunity to explore the behavioural factors that influence consumer preferences for zero-emission vehicles during the early adoption phase.

3.2. Experimental design and data collection

We conducted an experimental study through an online questionnaire developed using the Qualtrics platform and distributed by a commercial surveying service provider in April–May 2024. The questionnaire randomly assigned an initial stimulus to potential vehicle buyers selected among Italian consumers who hold a driving license and own a vehicle or intend to purchase a car within the next year. This allows us to achieve three treatment groups.

Respondents of the first group were asked to assess a BEV (existing product) related stimulus and, in the second, an FCEV (prospective product) related stimulus. Finally, the third one, called the "BLIND" group, answered after receiving a stimulus concerning the product category represented by zero-emission vehicles without specifying the technology. The questions following the initial stimulus remained consistent across all three groups.

The three variations of the stimulus had the same structure and formulation, placing respondents in a scenario requiring them to evaluate a potential future purchase (i.e., high psychological distance) and differing solely in the proposed technology and related stages of market diffusion (i.e., BEV, FCEV, or a blind option representative of the product category) (**Annex 1**).

Randomising respondents through the designed stimulus allowed us to evaluate changes in consumer inclinations between an existing product characterised by well-established technology (BEVs), an early pioneering stage technology (FCEV), serving as a prospective product, and the broader product category of zero-emission vehicles.

To ensure respondents paid attention to the initial stimulus, a concluding verification question was included to test and include in the sample only respondents who were aware of the type of vehicles they evaluated. Additionally, we excluded respondents who completed the questionnaire in less than 5 min, as this was deemed the minimum reasonable time given the number of questions and the need for careful reflection on the concepts presented. After applying these exclusion criteria, we obtained 1071 valid respondents: 354 in the BEV group, 351 in the FCEV group, and 366 in the Blind group. Table 1 presents the demographic characteristics of the respondents.

The three groups are balanced in gender distribution, with each group comprising approximately 50 % male and 50 % female participants. The groups show a higher concentration in the over-35 age and higher education groups, aligning with the general car-owner demographics in Italy (ISTAT, 2023).

Random sampling ensured homogeneity across the groups regarding gender, age, and education and enabled robust cross-sample comparisons (Table 1).

3.3. Measures

Each questionnaire began by introducing the focus of the survey and the objective to capture respondents' opinions on BEVs in group 1, FCEVs in group 2, and the zero-emission vehicles category in group 3. After the opt-out (driving license and car ownership) and demographic questions, the survey included 31 items designed to measure the constructs included in the conceptual framework (see Fig. 1). Environmental Values, Attitude, RF and RA, and Familiarity were measured using a seven-point Likert scale (1 = strongly disagree, to 7 = strongly

Table 1
Respondents' profile.

Respondent Profile		BEV		FCEV		BLIND	
Variable	Sub-variable	Abs	%	Abs	%	Abs	%
Gender	Female	178	50,3 %	171	48,7 %	181	49,5 %
	Male	176	49,7 %	180	51,3 %	185	50,5 %
Age (in years)	18–35	19	5,4 %	33	9,4 %	15	4,1 %
	35–54	185	52,3 %	170	48,4 %	186	50,8 %
	Over 54	150	42,4 %	148	42,2 %	165	45,1 %
Education Level	Middle school	16	4,5 %	17	4,8 %	23	6,3 %
	Professional college	173	48,9 %	184	52,4 %	188	51,4 %
	Postgraduate degree	165	46,6 %	150	42,7 %	155	42,3 %
Total respondent		**354**	**100,0 %**	**351**	**100,0 %**	**366**	**100,0 %**

agree), with respondents rating their level of agreement with each statement.

In detail, the *Environmental Values* construct assesses personal values influencing behaviour towards zero-emission vehicles using six items developed by Haws et al. (2014) in line with recent studies (Sreen et al., 2023) in the field of green purchasing behaviours.

Familiarity construct, aimed at identifying the respondent's level of knowledge regarding the subject of each questionnaire, was operationalised using three items derived from the study of Gefen et al. (2000).

The "*reasons*" are context-specific factors that vary from one product to another, and this makes the identification of the constructs that can accurately measure the RF and the RA particularly challenging, given the intricacy and diversity of these motivations. Previous studies have often referred to extant literature to identify the "reasons" and have measured them through countless modalities, such as observed or latent variables, first or second-order variables, etc. (Sahu et al., 2020). The type of variables considered depends mainly on the kind of behaviour to be analysed and the setting considered each time.

As for the *Reasons For* we identified three key variables that, according to the literature, are the most influential determinants of consumer tendencies toward zero-emission vehicles: (i) **environmental advantages** (RfEnv), assessing the importance of having a low-emission vehicle, measured using four items adapted from Zhu et al. (2023); (ii) **economic advantages** (RfSaving), evaluating respondents' perceptions of zero-emission vehicles being more cost-effective compared to traditional combustion vehicles, particularly in terms of fuel savings, measured with three items from Claudy and Peterson (2014); and (iii) **governmental subsidies** (RfAids), assessing with three items the importance of benefiting from national subsidies to lower the purchase price of zero-emission vehicles (de Oliveira et al., 2022; Degirmenci and Breitner, 2017; Krupa et al., 2014).

Similarly, the inhibitors of consumer behaviour toward zero-emission vehicles classified as *Reasons Against* were: (i) long charging or **refuelling times** (RAtime), operationalised using three items adapted from Carley et al. (2013), Chen et al. (2021) and Degirmenci and Breitner (2017), (ii) limited **driving range** and associated range anxiety (RaRange), measured using a three-item scales from Chen et al. (2021) and Eccarius et al. (2023), and (iii) insufficient availability of charging or **refuelling stations** (RaRefil), measured using a three-item scales from Wiedmann et al. (2011).

Attitude, a predictor of intention in BRT (Westaby, 2005) that refers to a "psychological tendency that is expressed by evaluating a particular entity with some degree of favour or disfavour" (Eagly and Chaiken, 1993, p. 1), was measured using a three-item scale adapted from Claudy et al. (2015).

To ensure consistency in the translation process, as recommended in previous studies employing similar survey methodologies (Qian et al., 2023), we utilised the back-translation method (English--Italian-English). Specifically, one linguistic expert translated the items into Italian, while another independently translated them back into English. Any discrepancies between the original and back-translated versions were carefully reviewed and resolved to ensure conceptual equivalence across the two languages.

3.4. Data analysis

The data analysis was conducted using Stata version 18 (statistical software for data science).

Initially, *convergent validity* was tested by calculating the factor loadings of the items and the Kaiser-Meyer-Olkin (KMO) index. Factor loadings represent the correlation between an observed variable (item) and a latent factor, indicating how well a particular item is explained by the factor in the factor model. The KMO index, on the other hand, assesses sampling adequacy and confirms whether the data are suitable for factor analysis. All item loadings exceeded 0.7, and the KMO values were higher than 0.6, reflecting a desirable measurement model (Hair et al., 2014).

Next, Cronbach's α, Composite Reliability (CR), and Average Variance Extracted (AVE) were derived for each construct. All Cronbach's α values were above 0.8, while the CR and AVE values exceeded the recommended thresholds of 0.60 and 0.50, respectively, as suggested by Sekaran and Bougie (2016). These results surpass the indicated thresholds, supporting the validity of the constructs and demonstrating good internal consistency (Bagozzi and Yi, 1988). The results of the Convergent Validity are presented in Table 2.

As a second step, *discriminant validity* was calculated for each sample group using the method proposed by Fornell and Larcker (1981), which involves comparing the square root of the AVE for each factor with its correlation to other constructs. According to this method, discriminant validity is established when the empirical scores confirm that two variables predicted to be uncorrelated are indeed uncorrelated. Table 3 presents the results of this analysis, where the square root of the AVE for each construct was significantly higher than the correlations with other constructs, confirming that the measurements are distinct and unrelated, thus supporting the validity and independence of the variables in the study.

As a third step, we rigorously assessed measurement invariance across the three groups (BEV, FCEV and BLIND) through a construct-by-construct approach, as recommended by Cheung and Rensvold (2002) and Vandenberg and Lance (2000) to (1) avoid interference and convergence issues due to model complexity and high parameter counts (Byrne, 2010), (2) provide precise information about which specific constructs maintain invariance across groups, (3) allow for sensitive detection of non-invariance that might be masked in global models, and (4) yield stable parameter estimates. In detail, we tested for configural invariance (i.e., the same factorial structure across groups) and metric invariance (i.e., equal factor loadings across groups). Instead, we didn'*t*-test scalar invariance (i.e., equal factor loadings and intercepts across groups) and strict invariance (i.e., equal factor loadings, intercepts, and residual variances) due to the experimental nature of our study and the expected effects of the manipulations introduced across groups. Following the guidelines provided by Chen et al. (2021), besides global and construct specific goodness of fit (minCFI = 0,977 for

Table 2
Convergent validity results.

Construct	Variable Notation	BEV						FCEV						Blind					
		Factor Loading	Uniquness	KMO	Alpha	AVE	CR	Factor Loading	Uniqueness	KMO	Alpha	AVE	CR	Factor Loading	Uniquness	KMO	Alpha	AVE	CR
Fam	fam1	0,922	0,150	0,810	0,931	0,822	0,933	0,913	0,167	0,852	0,934	0,831	0,935	0,938	0,120	0,791	0,943	0,850	0,944
	fam2	0,935	0,126	0,757				0,946	0,105	0,715				0,940	0,117	0,782			
	fam3	0,957	0,085	0,687				0,962	0,074	0,668				0,965	0,069	0,685			
Rarang	rarang1	0,908	0,175	0,728	0,887	0,727	0,889	0,926	0,143	0,783	0,927	0,811	0,928	0,949	0,100	0,768	0,944	0,850	0,944
	rarang2	0,918	0,157	0,707				0,926	0,142	0,781				0,956	0,086	0,736			
	rarang3	0,884	0,219	0,795				0,950	0,097	0,701				0,941	0,115	0,808			
Ratime	ratime1	0,943	0,111	0,774	0,939	0,838	0,939	0,931	0,133	0,834	0,940	0,843	0,941	0,928	0,140	0,758	0,918	0,788	0,918
	ratime2	0,939	0,118	0,792				0,954	0,091	0,730				0,919	0,155	0,787			
	ratime3	0,951	0,097	0,743				0,952	0,094	0,737				0,935	0,127	0,735			
Rarefil	rarefil1	0,807	0,348	0,806	0,823	0,614	0,821	0,839	0,296	0,794	0,850	0,657	0,857	0,840	0,295	0,759	0,832	0,612	0,825
	rarefil2	0,886	0,216	0,663				0,906	0,179	0,665				0,893	0,202	0,669			
	rarefil3	0,886	0,215	0,662				0,884	0,218	0,698				0,862	0,257	0,716			
Rfsaving	rfsaving1	0,929	0,138	0,823	0,936	0,831	0,937	0,923	0,149	0,856	0,939	0,839	0,940	0,928	0,140	0,814	0,933	0,823	0,933
	rfsaving2	0,947	0,104	0,743				0,956	0,087	0,710				0,944	0,109	0,746			
	rfsaving3	0,950	0,098	0,732				0,953	0,092	0,719				0,946	0,105	0,736			
Rfenv	rfenv1	0,942	0,112	0,828	0,959	0,857	0,960	0,952	0,095	0,848	0,962	0,865	0,963	0,946	0,106	0,825	0,956	0,848	0,956
	rfenv2	0,963	0,073	0,802				0,954	0,090	0,854				0,959	0,081	0,802			
	rfenv3	0,948	0,100	0,874				0,966	0,068	0,829				0,943	0,110	0,879			
	rfenv4	0,922	0,150	0,887				0,918	0,158	0,889				0,915	0,163	0,905			
Rfaid	rfaid1	0,931	0,133	0,706	0,916	0,789	0,921	0,915	0,163	0,676	0,887	0,739	0,902	0,900	0,191	0,697	0,882	0,726	0,891
	rfaid2	0,891	0,206	0,840				0,852	0,274	0,834				0,860	0,261	0,793			
	rfaid3	0,952	0,093	0,660				0,941	0,114	0,637				0,939	0,119	0,637			
Valueenv	valueenv1	0,835	0,303	0,939	0,923	0,675	0,926	0,833	0,306	0,925	0,919	0,661	0,922	0,803	0,356	0,911	0,903	0,624	0,906
	valueenv2	0,894	0,201	0,879				0,897	0,195	0,885				0,892	0,205	0,858			
	valueenv3	0,904	0,183	0,865				0,884	0,218	0,881				0,854	0,271	0,883			
	valueenv4	0,852	0,275	0,919				0,829	0,313	0,943				0,791	0,374	0,923			
	valueenv5	0,827	0,316	0,918				0,804	0,353	0,939				0,838	0,297	0,911			
	valueenv6	0,805	0,353	0,924				0,828	0,314	0,925				0,780	0,391	0,915			
Attitutde	attitude1	0,951	0,096	0,751	0,944	0,848	0,945	0,918	0,157	0,750	0,906	0,764	0,906	0,938	0,121	0,758	0,929	0,814	0,929
	attitude2	0,935	0,126	0,832				0,905	0,181	0,792				0,928	0,139	0,795			
	attitude3	0,960	0,079	0,716				0,931	0,133	0,715				0,942	0,113	0,743			

Table 3
Discriminant validity results.

BEV									
AVE	0,822	0,727	0,838	0,614	0,831	0,857	0,789	0,675	0,848
Construct	Fam	Rarang	Ratime	Rarefil	Rfsaving	Rfenv	Rfaid	Valueenv	Attitude
Fam	1,000								
Rarang	0,034	1,000							
Ratime	0,019	0,517	1,000						
Rarefil	0,070	0,488	0,424	1,000					
Rfsaving	0,002	0,028	0,052	0,025	1,000				
Rfenv	0,005	0,031	0,062	0,015	0,338	1,000			
Rfaid	0,011	0,056	0,052	0,010	0,354	0,416	1,000		
Valueenv	0,067	0,003	0,005	0,011	0,106	0,077	0,114	1,000	
Attitude	0,023	0,100	0,122	0,052	0,351	0,806	0,568	0,151	1,000
FCEV									
AVE	0,831	0,811	0,843	0,657	0,839	0,865	0,739	0,661	0,764
Construct	Fam	Rarang	Ratime	Rarefil	Rfsaving	Rfenv	Rfaid	Valueenv	Attitude
Fam	1,000								
Rarang	0,048	1,000							
Ratime	0,080	0,481	1,000						
Rarefil	0,047	0,254	0,126	1,000					
Rfsaving	0,015	0,010	0,007	0,009	1,000				
Rfenv	0,034	0,003	0,006	0,008	0,296	1,000			
Rfaid	0,041	0,011	0,005	0,011	0,287	0,273	1,000		
Valueenv	0,033	0,003	0,002	0,001	0,074	0,083	0,137	1,000	
Attitude	0,068	0,023	0,020	0,007	0,344	0,690	0,443	0,217	1,000
BLIND									
AVE	0,850	0,850	0,788	0,612	0,823	0,848	0,726	0,624	0,814
Construct	Fam	Rarang	Ratime	Rarefil	Rfsaving	Rfenv	Rfaid	Valueenv	Attitude
Fam	1,000								
Rarang	0,017	1,000							
Ratime	0,033	0,625	1,000						
Rarefil	0,082	0,457	0,463	1,000					
Rfsaving	0,034	0,054	0,052	0,031	1,000				
Rfenv	0,023	0,055	0,058	0,015	0,308	1,000			
Rfaid	0,037	0,064	0,056	0,030	0,203	0,376	1,000		
Valueenv	0,018	0,037	0,023	0,005	0,038	0,091	0,123	1,000	
Attitude	0,052	0,124	0.162	0,073	0,312	0,756	0,485	0,190	1,000

Valueenv in the BLIND group; minTLI = 0,932 for Rfenv in the BEV group, maxRMSEA = 0,231 for Rfenv in the BEV group; maxSRMR = 0, 026 for Valueenv in the BLIND group), we assessed invariance using both the chi-square difference test and the difference in CFI (ΔCFI), considering invariance to be supported if the chi-square test is not significant or if the reduction in CFI is ≤ 0.01 (i.e. ΔCFI = CFI_metric - CFI_configural ≥ −0.01), even in the presence of a significant chi-square test. In line with our theoretical expectations, configural invariance was supported for all the non-just-identified constructs, indicating that the same factorial structure is valid across groups, as well as metric invariance, with ΔCFI values ranging from −0.001 to 0.081 (Fam ΔCFI = 0.055, Rarang ΔCFI = 0.041, Ratime ΔCFI = 0.062, Rarefil ΔCFI = 0.081, Rfsaving ΔCFI = 0.007, Rfenv ΔCFI = 0.031, Rfaid ΔCFI = 0.002, Valueenv ΔCFI = −0.001, Attitude ΔCFI = 0.023). Thus, the constructs retain the same meaning across the three groups despite the exposure to different stimuli.

Notably, the measurement model for each group demonstrated a *good fit with the data*, as indicated by the *fitting indices* consistently exceeding the recommended thresholds (Hair et al., 2014). The fit indices reported in Table 4 include RMSEA between 0 and 0.05, CFI >0.95, TLI >0.92, and SRMR between 0 and 0.05. These analyses confirmed the model's fit and convergent and discriminant validity, establishing the reliability and appropriateness of the measurement instruments used.

Table 4
Goodness of fit.

GOF	BEV	FCEV	BLIND
RMSEA	0,050	0,044	0,049
CFI	0,966	0,973	0,966
TLI	0,961	0,968	0,960
SRMR	0,039	0,041	0,047

3.5. Common method bias

Following Podsakoff et al. (2003), we addressed common method biases by adopting procedural approaches to minimise bias during data collection and applying statistical remedies ex-post to detect and eventually correct any residual bias.

Regarding the procedural approach, we employed an online survey platform that administered the questionnaire to the participants who consented to participate, ensuring their anonymity. Before starting the survey, participants were informed that there were no right or wrong answers, the data was solely for academic purposes, and that personal information would be kept strictly confidential. Emphasising these aspects helps alleviate participants' concerns and reduce social desirability biases.

As for the questionnaire design, we separated the measurement of predictor and criterion variables, which is crucial in studies exploring attitude relationships (Podsakoff et al., 2003). This procedure reduces the likelihood that respondents' answers to predictor variables will influence their responses to criterion variables, thereby eliminating the effects of consistency motifs, implicit theories and tendencies towards acquiescence or lenient responding (Podsakoff et al., 2003; MacKenzie and Podsakoff, 2012). Furthermore, as Tourangeau (2000) recommended, we employed well-established scales frequently used in previous studies to avoid ambiguous concepts, overly complex wording, and unclear syntax, all of which could confuse respondents and increase the risk of bias.

Concerning statistical methods for bias detection and control, we applied Harman's single-factor test. The results from each sample group showed that the maximum variance explained by a single factor was well below 40 % in every group, indicating that common method biases were not present in the data. Additionally, following Podsakoff et al. (2003), we conducted a confirmatory factor analysis (CFA) to assess whether a single factor could explain all data variances. The single-factor model demonstrated poor fit compared to the CFA of our hypothesised model, further confirming the insignificance of common method bias in our survey responses. Table 5 compares the single-factor CFA and the goodness-of-fit indices for our models.

4. Results and discussion

4.1. Structural equation model findings

Building on the proven solidity of the measurement model, we employed Covariance-Based Structural Equation Modelling (CB-SEM) to test our hypotheses and validate the proposed structural model. In this study, CB-SEM was preferred over the variance-based Partial Least Squares SEM (PLS-SEM) approach, as it is more suitable for theory testing and confirmation, whereas PLS-SEM is generally more appropriate for prediction and theory development (Dash and Paul, 2021; Rigdon et al., 2017). Consistent with prior studies (Chatterjee et al., 2024; Siddik et al., 2023), CB-SEM is particularly useful when the objective is to confirm or reject a theoretical model by assessing how well it reproduces the observed covariance matrix (Joreskog, 1982, p. 270; Chin et al., 2020). This methodological alignment fits the nature of our research, which is grounded in a well-established theoretical framework and aims to test a series of relationships drawn from prior literature. Even the newly introduced paths—such as those involving *familiarity*—are theoretically justified and supported by existing studies that connect this construct to *reasons* and *attitude*.

Using maximum likelihood estimation, the structural model demonstrated a good fit with the data, with RMSEA, CFI, TLI, and SRMR for each group matching the above-mentioned recommended thresholds (Hair et al., 2014) except for the BEV model with all the control variables, which yields fit indices that fall slightly short of the conventional thresholds. The findings are illustrated in Table 6, reporting β and p-values for each relationship of the model in each group, without and with control variables. While all the key relationships are confirmed in the structural models with and without control variables, notably, including control variables does not improve model fit. Overall, while socio-demographic variables are not irrelevant, they offer only a modest contribution in explaining the variance in perceptions and attitudes towards sustainable mobility technologies. In this respect, significant associations are primarily observed between familiarity and gender, familiarity and education, value orientation and age, and value orientation and education. These results support the view that ZEVs are high-involvement products of broad societal interest, with particular appeal among younger, well-educated males. Despite that, it is noteworthy that gender does not significantly affect overall attitudes towards sustainable mobility technologies in any of the three groups. More generally, the absence of significant direct effects of socio-demographic variables on overall attitudes suggests that demographic differences operate primarily through their influence on intermediary constructs such as familiarity, environmental values, and risk/benefit perceptions. This supports the relevance of the BRT-based mediation models in understanding how attitudes towards sustainable mobility technologies are formed.

As expected, the statistically significant relationships indicate that RF positively correlates with attitude, whereas RA shows a negative correlation. The analysis of the β coefficients reveals that, across all three groups, the cumulative statistically significant impact of RF exceeds that of RA; H1 is thus supported. This finding supports the insights from Liberman et al. (2002) in CLT, which suggest that temporal distance in decision-making leads to overestimating positive aspects compared to negative ones (Trope et al., 2007). This amplified confidence is confirmed for the evaluation and assessment of product category, existing products and prospective products, highlighting the universality of this relationship. This evidence helps clarify the conflicting findings regarding the magnitude of the relations between RF and RA and attitudes observed in previous studies (Claudy et al., 2015; Yadav et al., 2022; Jan et al., 2023) demonstrating that, in high-construal situations related to the cognitive evaluation of high-involvement products, independently by their technological specificity and market diffusion, overconfidence arises, leading to an overestimation of benefits because consumers find easier to generate pros versus cons cognitively (Herzog et al., 2007).

Across all three groups, Familiarity is negatively correlated with RA (except for Familiarity and RaRange in the BLIND group, where the p-value approaches the threshold at 0.051). This consistency across groups confirms that information-seeking processes (Sheth and Venkatesan, 1968) address the need to reduce uncertainty, a significant source of loss aversion (Kahneman and Tversky, 1979) and RA formation. H2a is thus supported. By demonstrating the significance of the role of information-seeking and analytical thinking (Familiarity) both in conditions where information is specific and readily available (BEV) or blurrier and more uncertain (BLIND group), our results highlight the universal role of familiarity in reducing perceived risk in cognitive process associated with high-involvement products by strengthening previous evidence resulting from studies on non-durable common goods (Xu and Zeng, 2022). This indicates that even when information is more abstract and, thus, less precisely assessable, RA's cognitive process is rooted in a psychological framework that includes concepts such as sensemaking and psychological coherence (Claudy et al., 2015). Within this framework, individuals make sense of the information available before acting (e.g., Thomas et al., 1993) and interpret them based on self-concept coherence (e.g., Nowak et al., 2000). Thus, prior knowledge and experience are fundamental in providing meaning and coherence to evaluations, supporting the alternatives and justifying pro-environmental actions.

Regarding H2b, our results confirm the expected positive relationship between familiarity and RF. This relationship is consistently observed across all three RFs in the BLIND group (where all β are positive and p-values <0.05), but not in the BEV group (all the p-values >0.05). To interpret this result, we should first highlight that RF and RA are not mirror constructs, and the underlying cognitive processes differ significantly (Claudy et al., 2015), explaining why the impact of familiarity on RF diverges from that on RA. The evaluation of benefits in the context of green products is tied to value-based considerations (Khan and Mohsin, 2017; Ng et al., 2024), and thus the formation of RF does not happen independently from people's beliefs (Claudy et al., 2013) or deep compatibility with personal values (e.g. Garcia et al., 2007; Karahanna et al., 2006; Kleijnen et al., 2009). In scenarios where

Table 5
Single-factor model comparison with study model.

GOF	BEV		FCEV		BLIND	
	Internal Model	Single Factor Model	Internal Model	Single Factor Model	Internal Model	Single Factor Model
RMSEA	0,05	0,203	0,044	0,208	0,049	0,201
CFI	0,966	0,403	0,973	0,341	0,966	0,387
TLI	0,961	0,361	0,968	0,294	0,96	0,344
SRMR	0,039	0,194	0,041	0,199	0,047	0,188

Table 6
Structural equation model results.

Path Description	Independent Variable	Dependent Variable	BEV		FCEV		Blind		Hypothesis Paths Conclusion
			Beta without controls	Beta with controls	Beta without controls	Beta with controls	Beta without controls	Beta with controls	
Effects of Reasons Against on Attitude	Rarang	Attitude	−0,113*	−0,115*	−0,021	−0,029	0,068	0,057	HP1: Supported
	Ratime		−0,061	−0,052	−0,003	−0,012	−0,194***	−0,176**	
	Rarefil		−0,025	−0,028	−0,105*	−0,081	−0,076	−0,093	
Effects of Reasons For on Attitude	Rfsaving	Attitude	−0,024	−0,026	0,060	0,059	0,049	0,049	
	Rfenv		0,653***	0,651***	0,567***	0,578***	0,584***	0,578***	
	Rfaid		0,258***	0,263***	0,163***	0,157***	0,180***	0,185***	
Effects of Familiarity on Reasons Against	Fam	Rarang	−0,149**	−0,160**	−0,236***	−0,182**	−0,099	−0,087	HP2a: Supported
		Ratime	−0,100*	−0,112*	−0,32***	−0,229***	−0,140**	−0,136**	
		Rarefil	−0,139***	−0,126***	−0,147***	−0,148***	−0,178***	−0,144***	
Effects of Familiarity on Reasons For	Fam	Rfsaving	−0,036	−0,022	0,073	0,077	0,136**	0,134**	HP2b: Supported
		Rfenv	−0,004	0,042	0,127*	0,101	0,109*	0,117*	
		Rfaid	0,021	0,043	0,162**	0,141*	0,135**	0,107*	
Effects of Values on Reasons Against	Valueenv	Rarang	−0,023	−0.036	−0,029	−0,035	−0,330**	−0,324**	HP3b: Supported
		Ratime	−0,054	−0.059	0,008	−0,007	−0,221*	−0,230*	
		Rarefil	−0,036	−0.047	0,007	−0,001	−0,045	−0,068	
Effects of Values on Reasons For	Valueenv	Rfsaving	0,455***	0.464***	0,335***	0,321***	0,281**	0,283**	HP3a: Supported
		Rfenv	0,484***	0.475***	0,348***	0,350***	0,536***	0,535***	
		Rfaid	0,543***	0.563***	0,553***	0,538***	0,581***	0,610***	
Effects of Familiarity on Attitude	Fam	Attitude	0,030	0,031	0,031	0,045	0,022	0,038	Hp4: Rejected
Effects of Values on Attitude	Valueenv	Attitude	0,169***	0,0169***	0,209***	0,211***	0,240***	0,241***	Hp5: Supported
Effects of gender on latent variables	gender	Valueenv		−0,106		0,055		−0,126	
		Fam		0,851***		0,809***		0,982***	
		Rarang		0,093		−0,403**		−0,086	
		Ratime		0,167		−0,686***		0,100	
		Rarefil		−0,070		−0,013		−0,214	
		Rfsaving		−0,068		−0,053		−0,011	
		Rfenv		−0,310		0,211		−0,104	
		Rfaid		−0,034		0,135		0,219	
		Attitude		−0,109		−0,096		−0,129	
Effects of education on latent variables	education	Fam		0,454***		0,182		0,411**	
		Valueenv		0,225*		0,233**		0,013	
		Rarang		0,112		−0,032		−0,169	
		Ratime		0,034		0,009		−0,240*	
		Rarefil		−0,055		0,105		−0,227*	
		Rfsaving		−0,124		0,142		0,097	
		Rfenv		−0,188		0,041		0,099	
		Rfaid		−0,286*		0,119		0,154	
		Attitude		0,083		−0,049		−0,107	
Effects of age on latent variables	age	Valueenv		0,244**		0,012		0,221**	
		Fam		−0,325*		−0,152		−0,225	
		Rarang		0,102		−0,101		−0,139	
		Ratime		0,106		−0,074		0,066	
		Rarefil		0,074		0,254**		0,040	
		Rfsaving		−0,111		0,061		0,006	
		Rfenv		0,004		0,197*		−0,008	
		Rfaid		−0,137		−0,252*		−0,105	
		Attitude		−0,105		−0,057		−0,104	
RMSEA			*0,052*	*0,054*	*0,044*	*0,041*	*0,050*	*0,049*	
CFI			*0,964*	*0,954*	*0,972*	*0,972*	*0,965*	*0,960*	
TLI			*0,958*	*0,946*	*0,968*	*0,967*	*0,960*	*0,953*	
SRMR			*0,077*	*0,083*	*0,047*	*0,051*	*0,073*	*0,074*	

Note: ***p < 0.001, **p < 0.01, *p < 0.05, all in one tail.

information is readily available to consumers, such as existing products (i.e., the BEV group), the elaborated information is technical, specific and linked to concrete characteristics, which may conflict with the more idealistic and purely value-driven dimension that guides the formation of RF. In this case, the prior experience developed might not support an enhancement of the RF. However, instead of negatively impacting the dependent variable, it generates an agnostic and sceptical response, providing non-significant relationships.

This dynamic differs when consumers evaluate the product category that is characterised by greater uncertainty (Laroche et al., 2010). In such cases, where information is less accessible, scepticism toward specific technical features lacks a solid foundation. Here, the perceived familiarity with the product category enhances the perception of the benefits associated with the technology, demonstrating a stronger role for familiarity in shaping RF.

Consistent with our expectations for H2b, H3a is supported as environmental values are significant predictors of RF, with this relationship being statistically significant across all three groups (where all β are positive and p-values <0.05). These findings confirm that RF, particularly in the context of green products, are driven by value-based considerations (Khan and Mohsin, 2017; Ng et al., 2024). In this regard, prior studies' discordant results can be explained by considering the effect of CLT (Liberman and Trope, 1998) as the temporal distance influences the RF shaping process, leading consumers to adopt a more idealistic cognitive approach (Trope et al., 2007) and be less tied to analytical and rational dimensions. The universality of this relationship is proven by its significance and direction across the product category (BLIND), the prospective product (FCEV) and the existing product (BEV).

Values are negatively associated with RA at the product category level but not universally, thus H3b is supported. Specifically, in the BLIND group, two out of three relationships are statistically significant with negative β coefficients. In contrast, in the FCEV and BEV groups, the relationships do not exhibit p-values <0.05. In line with the theoretical predictions, the cognitive process underlying the formation of RA is grounded in the analytical evaluation of the phenomenon, wherein uncertainty and loss aversion play a crucial role in shaping the cognitions individuals will use to justify their behaviour.

In contexts of "handled risk", which is typical for existing products, value-based considerations do not mitigate perceived risk, as the management of uncertainty shifts toward information-seeking and knowledge-based processes. Conversely, when evaluations are made at the product category level, characterised by "inherent risk" and greater vagueness (Bettman, 1973), rational and analytical assessments become more challenging (Laroche et al., 2010). In such cases, part of the cognitive process shifts towards an idealistic dimension, partially driven by values. This result provides insight into the mixed findings in previous studies, where the relationship between environmental values and RA has shown inconsistent outcomes in terms of both significance and direction (Dhir et al., 2021; Sreen et al., 2023; Chatterjee et al., 2022) that might be attributable to differences into assessment from product category to existing products.

Familiarity is not positively associated with attitude; thus, in our setting, H4 is not supported. Despite positive βs across all three groups, this relationship is consistently not significant with p-values >0.05. This suggests that experience and knowledge of a given product, particularly in the case of high-involvement products characterised by risky and expensive purchase decisions, require more complex cognitive processing to translate into behavioural impact. This is partially supported by the previously identified effect concerning the relationship between familiarity and the reasons. These findings confirm that information enters the decision-making process and, before acting, the individuals interpret it under the framework of cognitive mechanisms such as sensemaking (e.g., Thomas et al., 1993) and psychological coherence (e.g., Nowak et al., 2000). Then, they need to be processed before forming an attitude.

Values are positively associated with attitude; thus, H5 is supported. Positive and statistically significant coefficients among all groups confirm the universality of this relationship.

This direct relationship integrates the mediated impact through reasons, underscoring the crucial role of values in shaping behaviours in the context of green products and providing additional insights into understanding the influence exerted by values, one of the antecedents of behaviours (Groening et al., 2018). In other words, environmental values not only influence the construction of reasons that further support decision-making but also directly activate attitudes toward the product (Bargh et al., 1996).

Our results indicate that this effect holds both for product category and (existing and prospective) products. However, the β values show a decreasing trend across groups, moving from BLIND to BEV (e.g., BLIND $\beta = 0.24$; FCEV $\beta = 0.209$; BEV $\beta = 0.169$). This suggests that in contexts where information is scarce or ambiguous (e.g., BLIND and FCEV), values play a more pronounced role in shaping attitudes, compensating for the lack of a robust rational-analytical process grounded in informational clarity. Conversely, when the context is more tangible and information is more specific and readily available (e.g., BEV), the relative impact of values diminishes, suggesting that more practical considerations emerge in the cognitive processes driving behaviour.

4.2. Mediation analysis

Mediation analyses helped further capture the underlying mechanisms across values, familiarity, reasons, and attitudes. In line with the conceptual framework highlighted in Fig. 1, we examined the mediation role of reasons between Values and Attitude, as well as Familiarity and Attitude, using both the Sobel approach (1986) and the Monte Carlo method to estimate confidence intervals for indirect effects.

First, we explored significant mediation effects using Sobel's z test. Second, for the relevant paths, examination of the sampling distribution of the indirect effect indicated that the critical normality assumption of the Sobel approach (MacKinnon et al., 2002) was satisfied. In particular, we employed a multi-method strategy, generating 1000 bootstrap replications of the mediation pathway to ensure the robustness of our conclusions, even in the presence of minor deviations from normality (Preacher and Hayes, 2008). For instance, in line with Zhao et al. (2010), we investigated the mediation between Valueenv, Rfsaving, and Attitude within the BEV group, collecting the following evidence: 1) the distribution of the indirect effect was approximately normal, as indicated by skewness (0.186) and kurtosis (3.008) values; 2) although the Shapiro-Wilk test was marginally significant ($p = 0.049$), the skewness and kurtosis tests were not ($p = 0.060$); 3) as recommended by Hayes (2009), we complemented the Sobel test with a bootstrap approach, comparing confidence intervals obtained using both the delta method (0.177–0.384) and the percentile bootstrap method (0.156–0.422), both approaches confirming the 95 % significance of the indirect effect.

To further strengthen the validity of our findings, we complemented the analysis with a Monte Carlo analysis on the full model, which yielded highly consistent results, thereby reinforcing the robustness of our conclusions. This methodological choice is particularly appropriate for our complex SEM model, which includes multiple latent variables and requires the examination of 36 distinct mediation pathways across three groups (BEV, BLIND, FCEV). While nonparametric bootstrapping with 5000 resamples is often considered the gold standard (Shrout and Bolger, 2002), simulation studies have demonstrated that the Monte Carlo method yields confidence intervals that are substantively equivalent to those obtained via bootstrapping (Preacher and Selig, 2012), with the added advantages of greater computational efficiency and comparable statistical accuracy. Compared with the delta method, which assumes normality, the Monte Carlo method maintains more appropriate control over Type I error and achieves statistical power comparable to that of bootstrapping (MacKinnon et al., 2004). Moreover, like bootstrapping, the Monte Carlo approach equally allows handling non-normal distributions of indirect effects, which is a particularly relevant issue in mediation analysis, where the product of coefficients is often asymmetric (Tofighi and MacKinnon, 2016), but -for complex models-it also presents fewer convergence issues due to extensive parameterisation (Muthén and Muthén, 2002). This methodological robustness is especially pertinent in our study, which systematically compares mediation effects across several theoretical constructs, multiple mediators, and distinct groups—an analytical design aligned with the practical considerations in mediation analysis emphasised by Shrout and Bolger (2002).

Table 7 shows the Monte Carlo results, highlighting the relative sizes of the indirect (i.e., mediated) and direct paths and classifying the mediations according to Baron and Kenny (1986).

Regarding the value-reasons-attitude relationship, both Reasons for Environment and Reasons for Aid partially mediate the relationship between value and attitude across all three groups. For example, in the BEV group, the Value-Attitude relationship shows a significant direct effect with $\beta = 0.169$ (p-value <0.001), alongside a significant indirect effect through Rfenv with $\beta = 0.317$ (p-value <0.001).

In the BLIND group, the mediation also involves Reasons Against Time (RAtime), indicating an even stronger net impact of RAtime on attitude as its direct effect is partially offset by the positive mediating effect of 0.043, which softens the overall impact.

These findings further clarify the relationship between Values and Attitudes. The results corresponding to H5 underscored the universal direct influence of values in shaping attitudes toward green products,

Table 7
Mediating test results.

Group	IV	Mediator	DV	$b_{(IV-M)}$	$se_{(IV-M)}$	$b_{(M-DV)}$	$se_{(M-DV)}$	$b_{(IV-DV)}$	$se_{(IV-DV)}$	Indirect effect	Total effect	Proportion	Indirect effect CI	Significant	Mediation type
BEV	Fam	Rarang	Attitude	−0,149**	0,049	−0,113*	0,057	0,030	0,027	0,017	0,047	0,36	0,000 to 0,041	Yes	Complete Mediation
		Rarefil	Attitude	−0,139***	0,034	−0,025	0,078	0,030	0,027	0,003	0,033	0,098	−0,018 to 0,026	No	No Mediation
		Ratime	Attitude	−0,100*	0,047	−0,061	0,052	0,030	0,027	0,006	0,036	0,171	−0,004 to 0,021	No	No Mediation
		Rfaid	Attitude	0,021	0,058	0,258***	0,037	0,030	0,027	0,006	0,035	0,156	−0,024 to 0,036	No	No Mediation
		Rfenv	Attitude	−0,004	0,062	0,653***	0,037	0,030	0,027	−0,003	0,027	−0,101	−0,084 to 0,077	No	No Mediation
		Rfsaving	Attitude	−0,036	0,048	−0,024	0,04	0,030	0,027	0,001	0,031	0,028	−0,004 to 0,008	No	No Mediation
	Valueenv	Rarang	Attitude	−0,023	0,077	−0,113*	0,057	0,169***	0,045	0,003	0,172	0,015	−0,017 to 0,024	No	No Mediation
		Rarefil	Attitude	−0,036	0,051	−0,025	0,078	0,169***	0,045	0,001	0,17	0,006	−0,009 to 0,013	No	No Mediation
		Ratime	Attitude	−0,054	0,073	−0,061	0,052	0,169***	0,045	0,003	0,172	0,019	−0,008 to 0,020	No	No Mediation
		Rfaid	Attitude	0,543***	0,095	0,258***	0,037	0,169***	0,045	0,14	0,309	0,453	0,082 to 0,207	Yes	Partial Mediation
		Rfenv	Attitude	0,484***	0,1	0,653***	0,037	0,169***	0,045	0,317	0,486	0,652	0,186 to 0,452	Yes	Partial Mediation
		Rfsaving	Attitude	0,455***	0,079	−0,024	0,04	0,169***	0,045	−0,011	0,158	−0,07	−0,050 to 0,026	No	No Mediation
FCEV	Fam	Rarang	Attitude	−0,236***	0,062	−0,021	0,038	0,031	0,028	0,005	0,036	0,138	−0,013 to 0,025	No	No Mediation
		Rarefil	Attitude	−0,147***	0,04	−0,105*	0,051	0,031	0,028	0,016	0,047	0,333	0,001 to 0,036	Yes	Complete Mediation
		Ratime	Attitude	−0,320***	0,063	−0,003	0,034	0,031	0,028	0,001	0,032	0,032	−0,022 to 0,023	No	No Mediation
		Rfaid	Attitude	0,162**	0,061	0,163***	0,031	0,031	0,028	0,026	0,057	0,456	0,006 to 0,050	Yes	Complete Mediation
		Rfenv	Attitude	0,127*	0,05	0,567***	0,041	0,031	0,028	0,072	0,103	0,697	0,015 to 0,130	Yes	Complete Mediation
		Rfsaving	Attitude	0,072	0,051	0,060	0,037	0,031	0,028	0,004	0,036	0,121	−0,002 to 0,015	No	No Mediation
	Valueenv	Rarang	Attitude	−0,029	0,088	−0,021	0,038	0,209***	0,042	0,001	0,209	0,003	−0,007 to 0,010	No	No Mediation
		Rarefil	Attitude	0,007	0,056	−0,105*	0,051	0,209***	0,042	−0,001	0,208	−0,003	−0,015 to 0,013	No	No Mediation
		Ratime	Attitude	0,008	0,088	−0,003	0,034	0,209***	0,042	0	0,209	0	−0,007 to 0,007	No	No Mediation
		Rfaid	Attitude	0,553***	0,092	0,163***	0,031	0,209***	0,042	0,09	0,299	0,301	0,049 to 0,139	Yes	Partial Mediation
		Rfenv	Attitude	0,348***	0,074	0,567***	0,041	0,209***	0,042	0,198	0,407	0,487	0,112 to 0,287	Yes	Partial Mediation
		Rfsaving	Attitude	0,335***	0,075	0,060	0,037	0,209***	0,042	0,02	0,229	0,088	−0,004 to 0,049	No	No Mediation
BLIND	Fam	Rarang	Attitude	−0,099	0,05	0,068	0,049	0,022	0,025	−0,007	0,015	−0,452	−0,022 to 0,003	No	No Mediation
		Rarefil	Attitude	−0,178***	0,037	−0,076	0,064	0,022	0,025	0,014	0,035	0,387	−0,008 to 0,039	No	No Mediation
		Ratime	Attitude	−0,140**	0,047	−0,194***	0,054	0,022	0,025	0,027	0,049	0,559	0,007 to 0,054	Yes	Complete Mediation
		Rfaid	Attitude	0,135**	0,048	0,180***	0,037	0,022	0,025	0,024	0,046	0,529	0,006 to 0,047	Yes	Complete Mediation
		Rfenv	Attitude	0,109*	0,05	0,584***	0,039	0,022	0,025	0,063	0,085	0,745	0,006 to 0,122	Yes	Complete Mediation
		Rfsaving	Attitude	0,136**	0,045	0,049	0,035	0,022	0,025	0,007	0,028	0,234	−0,003 to 0,020	No	No Mediation
	Valueenv	Rarang	Attitude	−0,330**	0,101	0,068	0,049	0,240***	0,052	−0,023	0,217	−0,104	−0,063 to 0,009	No	No Mediation
		Rarefil	Attitude	−0,045	0,07	−0,076	0,064	0,240***	0,052	0,003	0,243	0,013	−0,010 to 0,021	No	No Mediation
		Ratime	Attitude	−0,221*	0,092	−0,194***	0,054	0,240***	0,052	0,043	0,283	0,152	0,006 to 0,093	Yes	Partial Mediation
		Rfaid	Attitude	0,581***	0,1	0,180***	0,037	0,240***	0,052	0,104	0,344	0,303	0,055 to 0,165	Yes	Partial Mediation
		Rfenv	Attitude	0,536***	0,102	0,584***	0,039	0.240***	0,052	0,313	0,553	0,566	0,194 to 0,439	Yes	Partial Mediation
		Rfsaving	Attitude	0,281**	0,09	0,049	0,035	0,240***	0,052	0,014	0,253	0,053	−0,005 to 0,038	No	No Mediation

$p < 0.05$ = *, $p < 0.01$ = **, $p < 0.001$ = ***.
IV: Independent Variable; DV: Dependent Variable; b:Beta; se: Standard Error; CI: confidence Interval.

overriding rational cognitive processes. The mediation analysis reinforces these findings and integrates prior research (e.g., Claudy et al., 2013) by demonstrating that values are also universally processed through cognitive mechanisms underpinning the formation of RF. This process results in an indirect effect on attitude via mediation through RF, aligning with recent evidence in BRT studies (Qian et al., 2023; Virmani et al., 2023).

As for the familiarity-reasons-attitude relationship, the mediation analysis provides new nuances concerning H4, revealing indirect effects of familiarity on attitude.

Table 7 illustrates that, across all groups, at least one reason mediates the relationship between familiarity and attitude. Full mediation effects were observed for specific constructs: RARange in the BEV group; RARefill, RfAid, and RfEnv in the FCEV group; and RfEnv, RfAid, and RAtime in the BLIND group.

Integrating these findings with the results from the SEM analysis - specifically the effects of familiarity on reasons (HP2a and HP2b) and attitude (HP4) - we can provide a clearer understanding of the role of familiarity in the consumer cognitive process. Building on previous studies (Witzling et al., 2015; Trumbo and O'Keefe, 2001), our findings confirm that experience and knowledge serve as foundational elements influencing attitude. This influence of familiarity on attitude is mediated through the operationalisation of prior information and knowledge within the process of constructing reasons. The observed mediations expand upon previous research (Rizzi et al., 2020; Fischer and Frewer, 2009), emphasising that familiarity establishes an analytical basis for developing reasoning processes, which subsequently contribute to attitude formation. In other words, the effect of familiarity on attitude largely depends on the rational cognitive processes underpinning the construction of reasons.

Finally, it is important to note that, while these results highlight the presence of mediated effects, they do not support the assumption of a universally valid mediation relationship, as differences emerge across groups (e.g., full mediation through RFEnvironment and RFAid in both FCEV and BLIND versus full mediation effect through RARange in BEV). Nevertheless, it is worth emphasising that all three groups exhibit mediated effects of familiarity on attitude, consistently demonstrating a positive β. This reinforces the premise that familiarity indirectly contributes to attitude formation, further underlining its role in shaping consumer cognitive processes.

5. Implications

5.1. Theoretical implications

Building on extant research that highlights the importance of prior experience in shaping consumer behaviour (Fischer and Frewer, 2009; Herzog et al., 2007), this study introduces familiarity within the BRT model (Westaby, 2005) as a valuable predictor of reasons and attitudes. Our findings reveal that, in the context of high involvement products, familiarity plays a critical role in alleviating uncertainty and concerns surrounding the decision, key factors in the development of RA for both (existing and prospective) products and product categories. Conversely, familiarity's influence on RF is limited to either the product category (e.g., BLIND) or the prospective product (e.g., FCEV). This indicates that when specific information is available, it might conflict with value-driven or idealistic inclinations; therefore, familiarity loses significance, leading to a more sceptical consumer approach.

Furthermore, we identify recurring mediation effects of reasons in the relationship between familiarity and attitude. This result aligns with earlier studies (Sidiras and Koukios, 2004; Rizzi et al., 2020), highlighting the varying impact of information exposure depending on the nature of the product, from impulsive purchases to complex and costly ones. Our findings suggest that exposure to information in complex purchase decisions effectively influences attitudes through reasons. This evidence underscores the distinction between familiarity and values: while environmental values play a pivotal role in promoting green behaviours by bypassing rational-cognitive processes and directly influencing attitudes universally, familiarity affects attitudes exclusively through the mediation of reasons.

Building on this, our study also contributes to delving deeper into the cognitive processes underlying the formation of reasons and exploring their dynamic across the product category, and prospective and existing products. This analysis highlights both universal and case-specific relationships in the formation of reasons, yielding significant insights into understanding the nature of RA and RF and their hidden interaction with other constructs. Firstly, we found that RF is a value-driven construct, where environmental values act as predictors regardless of the product's technological specificity and level of market diffusion, which enriches the existing literature on RF (Kautish et al., 2024; Khan and Mohsin, 2017; Garcia et al., 2007; Pieters and Zeelenberg, 2005) by demonstrating the universality of this relationship. Conversely, RA is a more analytically and rationally driven construct, with stronger relations with familiarity than values because of the effectiveness of knowledge in mitigating uncertainty and loss aversion (Kahneman and Tversky, 1979; Neumann and Böckenholt, 2014). Interestingly, in the context of product category-level analysis, values and familiarity have similar effects in reducing RA and intensifying RF. However, at the product-specific level, their roles become antithetical: familiarity reduces RA, while values amplify RF. This finding further illustrates the distinct nature of RF and RA constructs (Westaby, 2005; Claudy et al., 2015), explaining how evaluative-behavioural processes vary across product category, prospective products and existing products that evoke rationality and idealism differently.

As a third key contribution, our study draws attention to the importance of temporal distance, as highlighted by CLT (Liberman and Trope, 1998), in applying BRT. Despite its established status in behavioural research, CLT's core insights are rarely considered in the interpretation of BRT results. We investigate consumer responses in contexts where temporal distance is consistently high across all three groups, a fundamental aspect in interpreting the relationships among BRT variables, particularly between reasons and attitudes. Specifically, we demonstrated that temporal distance fosters overconfidence (Liberman et al., 2002; Trope et al., 2007), amplifying the effect of RF on attitude compared to RA. This finding is valuable for interpreting conflicting results in recent literature (Yadav et al., 2022; Jan et al., 2023; Qian et al., 2023), as caused by weak comparability of studies on different technologies or adoption processes (Claudy et al., 2015) because of their differences in the temporal distance among the evaluated scenarios.

Finally, our study contributes to the foundation of BRT literature by investigating its relations across product category, prospective products and existing products, which are three typical subjects in technology adoption studies. This approach shows that BRT reveals different cognitions when the consumer shifts from a product category to a prospective or existing product, proving the adaptive nature of the cognitive processes influencing the adoption of emerging technologies, particularly within the context of green products.

By doing so, the study delves deeper into the underlying mechanisms shaping the formation of reasoning constructs, offering enhanced insights into their nature and unravelling universal and category or product-specific relationships.

5.2. Practical and managerial implications

This study serves as a foundation for researchers to delve into the behavioural aspects of sustainable mobility adoption. However, its contribution extends beyond the specific context, offering insights applicable to green innovation and technology adoption across various domains.

The development processes for new technologies aimed at reducing greenhouse gas emissions often start at a product category level. They subsequently undergo a grounding process, transitioning through the prospective product stage and ultimately reaching the existing product stage. Despite their promising environmental benefits and the initial consumer enthusiasm they often generate, the adoption of such technologies is rarely seamless.

Thus, it is crucial for companies, on the one hand, to properly understand consumers' desiderata and how these evolve throughout the different stages of product development, and, on the other hand, to identify the most effective marketing strategies and communication levers to engage end-users across the technological evolution and diffusion.

Concerning the former, our study offers important implications for R&D management. In particular, our findings highlight the need for companies to interpret survey results related to early-stage products with caution. Firms initiating the design and development of new product concepts often rely heavily on consumer data to identify emerging or latent needs and trends. These processes are essential for defining product features that capture consumer interest and for guiding prototyping and development decisions aligned with market preferences.

However, as our analysis demonstrates, the *reasons for* variables tend to be overestimated relative to the *reasons against* when consumers evaluate a product from a position of high psychological distance. This suggests that firms should treat survey results with prudence when there is a substantial gap between the evaluation context and an actual purchase decision. Failing to account for this bias may lead to overly optimistic interpretations of market analyses, which may not be reflected in actual product uptake at launch.

Moreover, our findings indicate that the relationships among variables affecting consumer attitudes toward emerging technologies undergo significant shifts as the product evolves (e.g., differences between BLIND and BEV). This highlights the need for a feedback-loop dynamic, in which market insights inform ongoing product development adjustments.

In light of this, we emphasise the importance of adopting an iterative approach that continuously integrates consumer feedback throughout the product development process. Such an approach should enable firms to capture changes in consumer responses at various development stages and to adjust their offerings accordingly.

From a marketing and communication standpoint, our study provides further managerial insights. While companies may respond to a market "pull" logic, adapting products based on expressed consumer needs, this dynamic coexists with a "push" logic, in which firms proactively shape preferences, reduce consumer biases, and build trust around new technologies. This requires a carefully crafted communication strategy that targets the cognitive dimensions consumers - often unconsciously - employ in their reasoning and evaluation processes.

Our findings highlight the importance of tailored communication strategies that emphasise different cognitive drivers depending on the product's stage of development. As shown in our SEM results, the formation of *reasons* is strongly associated with *value and familiarity* at the product category level. Accordingly, when promoting products in the early stages of development, companies should combine value-oriented messaging with feature-based communication. This dual approach can help mitigate perceived risk (i.e., by lowering *reasons against*) and enhance the perceived benefits (i.e., by increasing *reasons for*).

As the product moves toward a prototype or market-ready stage, our results show that *familiarity* becomes a dominant predictor in its (inverse) relationship with *reasons against,* while *values* retain their relevance primarily in shaping *reasons for*. This suggests the growing importance of practical, feature-based communication aimed at increasing consumers' familiarity with the technology. Enhancing familiarity can mitigate loss aversion, which is commonly associated with high-involvement innovative purchase decisions, particularly in the context of green technologies.

Instead, value-driven communication can leverage the positive relationship between personal values and *reasons for*, thereby enhancing consumers' perception of the benefits that the new technology can offer.

In conclusion, our findings advocate for a targeted communication and consumer engagement model that is carefully aligned with the specific stage of technological development. Such a model should strategically activate the most relevant cognitive constructs at each phase of product development, facilitating more effective market entry and sustained consumer adoption.

Finally, this research reaffirms the pivotal role of environmental values in driving the green transition, fostering the integration of purely technocentric perspectives. This insight is particularly relevant for policymakers, underscoring the importance of implementing communication strategies, education campaigns and policy interventions that foster a value paradigm aligned with sustainability principles without leaving behind the final goal of facilitating the adoption of green technologies.

6. Conclusions, limitations, and further research

Our study revealed the factors influencing consumer inclination towards zero-emission vehicles and unravelled the cognitive processes that underpin consumer engagement across the category and specific products. More specifically, it compared BRT insights concerning three subjects typically used to engage consumers with green technology: *product categories*, *prospective products*, and *existing products*. As a result, this study offers novel insights into the underlying rationales of the BRT constructs, a better understanding of the nature of each variable and, ultimately, of the underlying process of information assimilation and evaluation.

Like any study, this study presents limitations and opportunities for complementary research.

Firstly, our study, aimed at investigating the differences that arise when evaluations shift from product category to prospective product to existing product, excluded the intention (the final construct of BRT) due to the inability to examine intention concerning products not yet available on the market. However, we recommend that future research integrate a longitudinal perspective on market-available products to validate our findings by incorporating the intention variable within the familiarity-extended BRT framework. In this regard, we emphasise that our study is the first to investigate the impact of familiarity on reasons and attitudes within a BRT framework, which warrants further exploration in subsequent studies adopting different research settings or non-cross-sectional logic.

Another valuable insight could result from the implementation of a longitudinal study which tracks consumers' intention at different stages of product development within the familiarity-extended BRT framework.

Concerning our sample and setting, it is essential to note that our study was conducted within a single country (Italy) and focused on zero-emission vehicles. While this approach provided greater homogeneity among respondents, extending the analysis to additional countries with different levels of market maturity of zero-emission vehicles (i.e., BEV), technologies and high-involvement products would be beneficial to confirm the generalisation of our insights. Moreover, the sample has a higher concentration in the over-35 age group and those with higher education, which can underrepresent younger potential adopters and people with different levels of information exposure. Therefore, future studies should achieve a sample that includes young respondents and education groups.

Concerning our methodological design and questionnaire administration, we positioned respondents at a similar level of temporal distance, aligning all participants with a decision projected moderately far into the future (based on CLT). Future studies could strengthen and extend our findings by examining how different levels of temporal distance influence the relationships between variables, potentially revealing varying impacts across distinct time horizons. In particular, further analyses could investigate the role of low temporal distance across the selected typologies of products on the relationship between reasons and attitude in the BRT framework.

CRediT authorship contribution statement

Vittorio Maria Garibbo: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Francesco Rizzi:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Marina Gigliotti:** Writing – original draft, Investigation, Conceptualization. **Eleonora Annunziata:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Marco Frey:** Resources, Project administration.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Chat GPT exclusively for language editing purposes, such as improving phrasing and correcting grammatical errors.

After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2025.146580.

Data availability

Data will be made available on request.

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