Social acceptance of sustainable energy technologies: the role of beliefs in driving acceptability and acceptance of mitigation and adaptation technologies

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Abstract

This dissertation explores the social-psychological foundations underlying the social acceptance of Sustainable Energy Technologies (SETs), i.e., crucial elements in climate change mitigation and adaptation. The research centers on an analysis of how beliefs about the technology to be adopted characteristics, the adoption contexts, the adopters themselves, and their interactions, influence the social acceptability and acceptance of these technologies. Positioning the research within the theoretical framework of normative influence, the study highlights how perceptions of major clusters of social-psychological factors, namely, necessity, moral obligation, social expectations, and emotional responses, intersect to drive acceptance. A multi-method series of studies combines meta-analyses, correlational methods, and experimental approaches to assess various SETs by integrating insights from strictly normative influence with socio-technical theories. By aligning technological advancement with these foundational beliefs, this dissertation provides theoretical understanding and practical strategies for embedding SETs in the public sphere as instruments of sustainable collective action, promoting collective aspirations and individual actionable pathways toward climate resilience.

Keywords

social acceptance, sustainable energy technologies, mitigation, adaptation, beliefs, social norms

Summary

List of abbreviations

UN_United Nations

IPCC_Intergovernmental Panel on Climate Change

SET_Sustainable Energy Technology

TRL_Technology Readiness Level

SRL_Societal Readiness Level

NIMBY_Not In My Back Yard

CO_2_Carbon Dioxide

SSH_Social Sciences and Humanities

TNC_Theory of Normative Conduct

PEB_Pro Environmental Behavior

PRISMA_Preferred Reporting Items for Systematic reviews and Meta-Analyses

NAT_Norm Activation Theory

RET_Renewable Energy Technology

STEM_Science, Technology, Engineering, and Mathematics

TPB_Theory of Planned Behavior

SRM_Solar Radiation Management

VBN_Value-Belief-Norm

ELM_Elaboration Likelihood Model

DV_Dependent Variable

IV_Independent Variable

CCS_Carbon Capture and Storage

IF_Impact Factor

GII_Global Innovation Index

APA_American Psychological Association

PNA_Psychometric Network Analysis

CAN_Causal Attitude Network

RMSEA_Root Mean Square Error of Approximation

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INTRODUCTION

The massive population growth over the past two centuries and the exponential increase in energy consumption, which has arisen since the first industrial revolution (mid-18th century), have led over the years to a staggering increase in pollutant emissions and consequent climate change. Nowadays, it is known that the problem of climate change is a central issue and a challenge for the world community, leading the United Nations (UN) to develop targets for more sustainable development (2030 Agenda; UN, 2015).

One of the latest IPCC reports on climate change (2023) documents the deterioration of all major elements of the climate system (e.g., atmosphere, land, and ocean), leading to frightening changes in climate. This condition is the cause of phenomena such as decreasing ice area, sea level rise, ocean acidification, and phenomena such as droughts, floods, or other natural disasters (IPCC, 2021). Rapid, far-reaching, and unprecedented changes are needed to limit global warming to 1.5°C above pre-industrial levels (IPCC, 2018). Even acting immediately and drastically, however, global warming will likely reach 1.5 °C above pre-industrial levels by 2040 and exceed 1.5 °C in the following decades, with severe consequences for human and non-human life (IPCC, 2018, 2022, 2023). Therefore, it becomes clear that, among the most effective strategies to combat climate change, consuming less energy and relying increasingly on sustainable technologies and sustainable energy technologies (SETs) is one of the most important ways forward. When we talk about SETs, we refer to technologies that can produce energy or directly impact the Earth’s ecosystem through their use. In contrast, we define sustainable technologies as those that, despite playing a central role in the ecological transition and climate change mitigation, do not produce energy or directly impact the ecosystem but use sustainable and renewable energy sources (e.g., electric vehicles). The development of new energy technologies, in addition to the adoption of those already available, offers us the opportunity to move away from fossil fuel-based forms of energy, promote the circular economy, reduce carbon emissions, decrease greenhouse gas levels, and de-carbonize the environment (Al-Ghussain, 2019). With the introduction of new SETs (Messerli et al., 2019), the UN goal would be to reduce carbon emissions in transport by 80 percent and oil use by 70 percent to achieve carbon neutrality by 2050. However, to achieve significant progress in the energy transition, it becomes crucial not only to focus on the development of such energy technologies but also to prioritize their acceptability and acceptance by citizens, potential users of these new technologies, via the identification of factors that mobilize people to use them (when possible) or at least socially and politically support them by actively promoting their awareness and diffusion. Therefore, considering SETs, parallel to the well-known Technology Readiness Level (TRL; Héder, 2017), the promotion and the advancement of the corresponding, less-known Societal Readiness Level (SRL; Schraudner et al., 2018) - originally proposed to assess the level of societal fit of a particular technology - is crucial to foster their global and local adoption (e.g., Neofytou et al., 2020). From this perspective, promoting social acceptance of SETs should be aimed at, among other things, reducing opposition to such energy initiatives. Phenomena such as NIMBY (Not In My Back Yard; Devine-Wright, 2005), indeed, hinder the adoption of such technologies both locally and globally (Devine-Wright, 2005, 2009), preventing their widespread acceptance. Working in order to even try to counter opposition to such energy technologies, hence, plays a crucial role in facilitating their acceptance and adoption.

More generally, the adoption of SETs can be seen as part of what Cologna and Siegrist (2020) consider to be environmental mitigation and adaptation behaviors: examples of mitigation behaviors are reducing emissions and supporting climate-related mitigation policies, including taxes and mitigation technologies; on the other hand, adaptation behaviors are preparatory actions at the individual level and supporting adaptation policies and technologies. As previously mentioned, the acceptability, acceptance, and subsequent adoption of energy technologies (both mitigation and adaptation) by individuals, organizations, and societies also fall under mitigation and adaptation behaviors (Huijts et al., 2012). Mitigation energy technologies, such as solar, wind, and biofuels, seek to act on the causes of climate change and aim to mitigate its effects by decreasing fossil fuel consumption, carbon production, CO_2 emissions, and greenhouse gas levels. On the other hand, adaptation technologies, such as solar radiation management interventions, focus on adapting human activities and the environment to climate change (Baum et al., 2022). Such adaptation technologies precisely fall under climate engineering or geoengineering (IPCC, 2014).

Even though Fischhoff et al. (1978) conducted the first study on the social acceptance of SETs in the 1970s, the issue received little attention until the 1980s and was not widely investigated until the 1990s. Among the first scholars to characterize the social acceptance of renewable and sustainable energy technologies in the 1980s was Carlman (1984), who stressed that factors such as wind turbine placement had a direct bearing on public, governmental, and regulatory approval. Despite this, social acceptance of renewable and sustainable energy technology was not well researched and was presented in an unclear and confusing manner until the end of the subsequent decade (Wüstenhagen et al., 2007). In fact, compared to the focus on pure technological innovation, research on the social acceptance of SETs is still lacking. This is clear when one considers that environmental policy initiatives launched in the 1970s and 1980s resulted in highly sophisticated but not necessarily socially acceptable technological advances.

Conceptual definitions in the social acceptance process

Moreover, there is a lack of common understanding of the concepts (Wolsink, 2012) due to multiple definitions contributing to their complexity (Dessi et al., 2022): Although acceptability, acceptance, and adoption are distinct and consequential concepts, these terms are often used incoherently, with a tendency to interchange them (Schumann, 2015). Only recently attempts to more systematically redefine acceptability, acceptance, and adoption of SETs, in order to disambiguate them, have been proposed (Bonaiuto et al., 2024), while inconsistency persists in establishing the situational, technical, and social-psychological factors that may influence any SET. Bonaiuto et al. (2023, 2024) conceptualized the "Social Acceptance" process of SETs as the process that leads people to the acceptability, and subsequently the acceptance and finally the adoption, of such technologies: "Acceptability" describes the favorable attitude toward a given technology (Brunson & Shindler, 2004; Fournis & Fortin, 2017; Dessi et al., 2022); "Acceptance", on the other hand, refers to the tripartite behavioral intention to socially and politically support, use, and purchase the energy technology (Dessi et al., 2022; Wüstenhagen et al., 2007); finally, "Adoption" completes the process of social acceptance and refers to the implementation of supportive, use, purchase behaviors toward it and/or its consistent use over time (i.e., respectively, behavior and habit; Bonaiuto et al., 2024).

Antecedents in the social acceptance process

Despite such increasing efforts in conceptualizing the social acceptance process, and although the need to increase the social acceptance of such technologies is well known (e.g., Köhler et al., 2019), the literature is still debating about the main factors that can promote it, by usually preferentially focusing on antecedent factors belonging to basically three different clusters. Several researchers have proposed the centrality of personal characteristics (such as values; Perlaviciute & Steg, 2015), or of contextual factors (such as social norms; Chan et al., 2022), or of characteristics related to the technology itself (e.g., in the Technology Acceptance Model; Davis et al., 1989), for promoting a widespread acceptance of SETs. However, no studies have yet been conducted that would attempt to understand in an all-encompassing way (i.e., across the above-mentioned three clusters of factors) the most influencing antecedents of the social acceptance of such technologies.

Thesis overview

Building on this broader context, this Doctoral Thesis seeks to identify what are the main drivers and barriers to the social acceptance of such energy technologies through a multi-method approach. Particularly, the Thesis investigates how beliefs related to the three above mentioned clusters impact SETs social acceptance, focusing in depth on the role of social comparison (contextual factor). Following the model proposed by Bonaiuto and colleagues (2023, 2024), the Thesis aims to elucidate the critical role of social norms, personal norm, and emotional responses in fostering the social acceptance of SETs. This contribution further emphasizes the pivotal role of acceptability in enhancing acceptance and mediating the influence of beliefs in promoting support, purchase, and adoption of SETs. Through an experimental approach, the Thesis then investigates the interrelation between contextual factors (descriptive social norms) and emotional responses in predicting the acceptance of these technologies. Starting with a broad perspective, the Thesis proposes a theoretical framework addressing the social acceptance of SETs, identifying key clusters of beliefs and, more specifically, the primary factors facilitating SETs support and adoption. Subsequently, as the focus becomes more specific, the Thesis aims to address a gap in the literature previously highlighted by Packard and Schultz (2023). This gap pertains to how individuals emotionally react to social comparison (conceptualized as descriptive social norms) and how these emotional reactions drive behavior. By contextualizing this theoretical framework within the social acceptance of SETs, this research offers initial insights into the impact of descriptive norms on individuals' emotions. It delineates which emotions are influenced by social comparison and how these emotions subsequently mediate and reinforce the effects of norms, encouraging pro-environmental actions.

The following Thesis is divided into 5 separate chapters that are briefly outlined below.

Chapter 1. This first chapter presents the theoretical framework in which this Thesis is situated.

First, the concept of social acceptance and the central role of Social Sciences and Humanities (SSH) in promoting an effective ecological and energy transition are introduced in the first paragraph. The first paragraph focuses on the main research approaches followed in this field so far (see Batel, 2020) and the theoretical models that have been applied. The structural differences between the social acceptance of mitigation and adaptation energy technologies are also highlighted. In the second paragraph, the main antecedents of the social acceptance of SETs (see Huijts et al., 2012) and some of the main categorizations of these antecedents (i.e., factors related to the adopted technology, the adoption context, and the adopting person) proposed in the literature (e.g., Bonaiuto et al., 2024; Perlaviciute & Steg, 2014) are presented. Methodological and structural differences between studies on the social acceptance of mitigation and adaptation SETs are then highlighted. In the third paragraph, focusing on contextual antecedents, the reference theory considered in Studies 2 and 3 of this Thesis (i.e., Focus Theory of Normative Conduct, TNC; Cialdini et al., 1990, 1991) is presented, detailing the role of social norms in guiding pro-environmental behaviors (PEBs). Lastly, the role of emotions elicited by social comparison in promoting PEBs is introduced, examining what drives individuals to conform to or deviate from social norms. The fourth and final paragraph presents a series of studies that specifically investigated the role of social norms in promoting the social acceptance of mitigation and adaptation SETs.

Therefore, Chapter 1 attempts to give a theoretical framework to the Thesis, answering the question of “what” by identifying the main focus of the research (i.e., social acceptance of

SETs; first two paragraphs), and “how” by explaining a possible means through which this subject can be understood (i.e., social norms; last two paragraphs).

Chapter 2. In Chapter 2, the first study of the research is presented. Study 1 consists of two series of meta-analyses designed to investigate the antecedents of social acceptability and acceptance of mitigation and adaptation energy technologies. The main purpose of the study is to identify the barriers and drivers to the acceptability and acceptance of these technologies and to rank them according to the effect size of their relationship with the social acceptability and acceptance. To do this, a quantitative literature review (meta-analysis) is conducted following the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses; Page et al., Moher et al., 2009; Page et al., 2021) guidelines. This study therefore aims to provide an overview as comprehensive and generalizable as possible to as many technologies as possible, of what factors influence the acceptability and acceptance of SETs.

Chapter 3. In chapter three the second study of the research is presented. The second study is a correlational study investigating the relationship between beliefs, acceptability, and acceptance of SETs. Notably, following the literature and results of Study 1, Study 2 aims to empirically test the theoretical model by Bonaiuto and colleagues (2023, 2024). Thus, three different beliefs afferent to the three clusters hypothesized by the theoretical model (perceived technological features, perceived contextual features, and self-perceived personal features) are examined, framing the study within the State of the Art related to normative influence, i.e., the Norm Activation Theory (NAT; Schwartz, 1968, 1977) and the TNC (Cialdini et al., 1990, 1991). Moreover, through graphical models (i.e., psychometric network analysis), it is tested how different acceptability characteristics may influence the acceptance of these technologies. Finally, the study aims to identify similarities and differences in the social acceptance process of mitigation and adaptation technologies through multigroup comparisons.

Chapter 4. In Chapter 4, the third study of this research is presented. The third study is an experimental study focusing on contextual beliefs and their role in influencing SETs' acceptability and acceptance. More specifically, building on the results of study 2, an experimental study is developed to examine the role of social influence (considered as descriptive social norms) in influencing people's emotional state and prompting them to enact pro-environmental behaviors (support of SETs). In the third study, unlike the first two studies, only mitigation energy technologies (and not adaptation energy technologies) are considered, for the sake of a first demonstration. This decision was driven by the findings from Study 2 - and partially from Study 1 - which showed that the social acceptance processes for the two SET categories tend to be similar. To simplify the process, Study 3 focused on technologies similar to each other that were more familiar to participants and that could be directly adopted. The results of this study could then lead to future research exploring the same effects for adaptation SETs.

Chapter 5. In the last chapter, a general discussion of the main results is provided, highlighting theoretical and applied implications, limitations and possible future directions.

CHAPTER 1

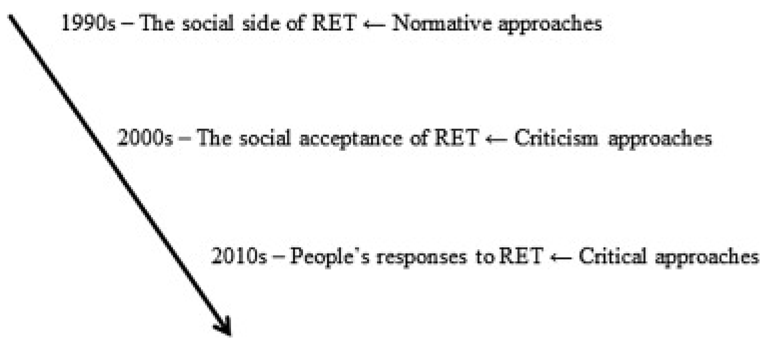
Literature overview

1.1. Social acceptance of mitigation and adaptation energy technologies

Climate change, like countless other longstanding problems afflicting humanity, is partly caused by humanity itself (IPCC, 2023). In 1863, John Stuart Mill stressed how in seeking personal benefit, indeed, humans engage in behaviors that ultimately harm the community (Mill, 1863). In the latter half of the last century, Garrett Hardin emphasized the need for greater public involvement in safeguarding common resources and promoting a just society. He highlighted how technical efforts alone are insufficient to achieve this goal, stressing the necessity for increased awareness and responsibility: "*The population problem has no technical solution; it requires a fundamental extension in morality*" (Hardin, 1968, p. 1243). As Hardin pointed out, mere technological advancement does not lead to effective and lasting changes unless it is integrated into the social framework and applied to promote the common good. Similarly, in the realm of climate change, the development of SETs is merely the first step toward meaningful change in climate, and only a widespread adoption by the community can make this change possible (Lennon et al., 2019): an adoption which should also be equitable, ensuring that diverse social and cultural groups equally benefit from implementing these technologies (Sovacool, Newell, et al., 2022).

As suggested by Steg and colleagues (2021), the Social Sciences and Humanities (SSH) role is crucial in understanding the factors that can promote the acceptance and widespread adoption of SETs. Moreover, SSH is vital in developing interventions to address these needs (Sovacool, 2014a; Sovacool et al., 2015). Over time, various studies have also emphasized the central role of SSH - specifically psychology - in finding meaningful responses to climate change, stressing the breadth of directions that can be taken in future research (e.g., Bonaiuto, 2023; Clayton et al., 2015). Fortunately, interest in these topics among SSH researchers – though still underdeveloped – has significantly grown, leading to a sharp increase in scientific publications in this field, intending to provide meaningful insights while enhancing two-way communication with the institutional stakeholders and policymakers (Sovacool, 2014b). Examining the past few decades of research, Batel (2020) has highlighted how different aspects have taken varying degrees of importance over time. Initial studies focused on reducing local opposition, often described as NIMBYism (e.g., Freudenberg & Steinsapir, 1991); later, the focus shifted toward issues of justice, transparency, and public participation (e.g., Barnett et al., 2012; Cass et al., 2010); finally, more recent work has examined power dynamics and systemic injustices (e.g., Batel et al., 2016). The study highlights a shift from a normative approach in the 1990s, which viewed social sciences as secondary to the development of SETs (in the study, named as renewable energy technologies, RET; see Figure 1); to a criticism approach in the 2000s focused on the social acceptance of SETs. More recently, a critical approach has emerged (from the past decade until today) to investigate individual responses to SETs (Figure 1).

Figure 1 - *SETs social acceptance waves of research*



Source: *Batel (2020).*

Similarly, Gaede and Rowlands (2018), through a bibliometric analysis of studies on the social acceptance of SETs, highlighted various theoretical and research trends, each associated with specific technologies. Their study reveals, for example, that wind energy is frequently examined concerning NIMBYism, while nuclear energy is more often studied through the lens of risk perception and personal values.

On the other hand, different disciplines have historically examined the social acceptance of SETs from distinct and often non-comparable perspectives. Additionally, it is well known that research in this field has not always produced outcomes which are useful for the community or represent advanced fundamental knowledge to enrich the State of the Art (see Sovacool et al., 2018), due to the lack of consistency in the definitions of the examined constructs and the adopted methodologies (Busse & Siebert, 2018). Furthermore, research in this area, being highly Western-centric (e.g., using Western, educated, industrialized, rich, and democratic sampling; WEIRD; Nielsen et al., 2017), underestimates the cultural implications related to the process of social acceptance in the "Global South" (van der Horst et al., 2021). This highlights a gap in the literature and demonstrates how the processes driving widespread adoption in regions where SETs are scarce – and which are most affected by the consequences of climate change – are often underestimated. To address these issues, several literature reviews and research agendas have been developed to identify the best path forward. For example, the review by Bessette and Crawford (2022), focusing on wind energy, suggests future pathways like those proposed by Sovacool and colleagues (2018), emphasizing also the importance of disseminating findings to stakeholders beyond the academic and scientific communities. Additionally, they advocate conducting comparative studies across different geographical regions and especially between different energy technologies. From this perspective, it is crucial to identify the factors that drive both social acceptance and widespread adoption of different type of technologies. In fact, while different technologies face not only economics and environmental sustainability criteria, but also unique psychological, social, political, and ethical challenges (e.g., Baur et al., 2022; Gaede & Rowlands, 2018; Sovacool et al., 2016; Verbruggen et al., 2010), they nonetheless undergo comparable complex social acceptance processes. For instance, mitigation energy technologies primarily face functional issues with only marginal ethical implications, while adaptation technologies, although they are not yet fully in use, raise major ethical concerns that complicate their rapid and broad adoption in the future (Corner & Pidgeon, 2010). Given their potential to directly influence the Earth's global ecosystem, indeed, adaptation technologies could have significant political and economic consequences for nations capable of deploying them (Sovacool, Baum, & Low, 2022a).

Despite these differences, both must be equally adopted by people, organizations, and local or global governments to promote massive and sustainable changes. Therefore, identifying the drivers behind behaviors toward different energy technologies would be crucial for designing systematic interventions to promote pro-environmental energy behaviors (Steg et al., 2021). Specifically, Perlaviciute, Schuitema, et al. (2018) suggest that recognizing social acceptance as a dynamic, multidimensional, and context-dependent process, rather than merely dismissing opposition as NIMBYism, may be a good practice for developing a more comprehensive understanding of the phenomenon.

It is, therefore, evident that there is a critical need to further explore the dynamics of social acceptance of these technologies in order to encourage their broader and widespread adoption and to ensure through a fair and inclusive technological transition – as Devine-Wright suggested in his research agenda (2022) – that the energy transition serves as a tool to foster equality and democracy.

There are hence numerous insights and pathways to be explored in order to ensure that SSH can contribute – alongside Science, Technology, Engineering, and Mathematics (STEM) fields – to combate climate change. Over and above understanding the psychological, social, ethical, and political dimensions of the acceptability and acceptance of these technologies, it is, therefore, subsequently essential to clarify what drives and hinders these processes, as Bonaiuto and colleagues (2024) highlighted.

1.2. What drives or hinders the social acceptance of sustainable energy technologies

As previously mentioned, despite the increasing body of research on the social acceptance of SETs over the past decades – with a notable surge in recent years alongside growing complexity (Batel, 2020) – there are still relatively few studies that attempted to conceptualize the process driving the social acceptance of these technologies. With some exceptions (e.g., Huijts et al., 2012), the literature also lacks comprehensive research that identifies the factors predicting social acceptance through a holistic approach. On the other hand, numerous studies have identified the role of specific predictors of social acceptance of specific technologies, thereby creating a substantial, though fragmented, body of research upon which a solid field of study can be built, effectively integrating theory and practical application.

Over the years, a broad array of research spanning psychology, sociology, and behavioral economics has investigated numerous factors that might promote or hinder the acceptability, acceptance, and subsequent adoption of such technologies. From a multidisciplinary perspective, these studies have examined social-psychological factors, such as the adopters' individual values (e.g., Perlaviciute & Steg, 2015), as well as economic and political factors, such as incentive policies (e.g., Capodaglio et al., 2016). This categorization can be partially linked to the one proposed by Griskevicius et al. (2010) regarding what drives pro-environmental behaviors. In that study, the authors proposed two frameworks for understanding what drives environmental behavior: environmental concern and economic rationality. The former suggests that individuals act in eco-friendly ways out of genuine care for the environment (in psychological terms, intrinsic motivations). In contrast, the latter implies that such behaviors are driven by economic incentives or the pursuit of personal gain (in psychological terms, extrinsic motivation).

Subsequent research has demonstrated that these factors (social-psychological and economic and political factors) independently operate and can interact to create a supportive or resistant environment for these technologies (Steg et al., 2015). Despite the centrality of purely contextual factors – like economic incentives or barriers – highlighted in various studies (e.g., Kowalska-Pyzalska, 2018; Puzzolo et al., 2016), from a psychological perspective it is more compelling to investigate social-psychological factors that can be leveraged to design targeted interventions aimed at raising awareness and promoting pro-environmental energy behaviors. Such a need to thoroughly investigate social-psychological factors has been made salient by Robert Gifford, who, about barriers to climate change mitigation and adaptation, mentions "*Structural barriers such as a climate-averse infrastructure are part of the answer, but psychological barriers also impede behavioral choices that would facilitate mitigation, adaptation, and environmental sustainability*" (Gifford, 2011, p. 290).

From a social-psychological perspective, some studies have classified the antecedents of social acceptability and acceptance of these technologies through critical reviews of previous literature, highlighting how these differ by "categories". For instance, Huijts et al. (2012) propose a systematization of the definitions of acceptability and acceptance and identify three main motives driving the acceptance of SETs. These are categorized into gain motives (based on the Theory of Planned Behavior, TPB; Ajzen, 1991), which include financial costs, social norms, perceived personal or societal risks, and benefits such as reduced environmental impacts; normative motives (rooted in NAT; Schwartz, 1968, 1977) based on moral obligations; and hedonic motives (Lindenberg & Steg, 2007), often linked to specific affective responses. The study highlights the central role of variables such as, respectively, perceived costs, risks, and benefits (De Groot & Steg, 2010); personal and social norms (e.g., Steg & De Groot, 2010); positive or negative emotional responses to the technology (Montijn-Dorgelo & Midden, 2008). But also trust and perceptions of fairness (respectively Terwel et al., 2009; Walker & Devine-Wright, 2008), as also noted in more recent reviews (e.g., Fytili & Zabaniotou, 2017); and knowledge and experience (O'Garra et al., 2008; Shaheen et al., 2008). Another foundational study that systematically categorized the social-psychological determinants of the social acceptance of SETs is the study of Perlaviciute and Steg (2014). Highlighting the importance of public acceptability to achieve a sustainable energy transition, they identify the main factors influencing the evaluation of these technologies. The study reports two main categories of determinants of social acceptability: psychological and contextual factors. The authors propose various levels of differentiation, beginning with the analysis of individual (e.g., Aldy et al., 2012; Pedersen & Persson Waye, 2004) and collective (contextual; Shackley et al., 2004) costs and benefits, emphasizing that both individual and collective factors contribute to influencing the acceptance of energy technologies. The study also identifies a marked differentiation between factors related to the technology and its adoption context, such as environmental impact, safety, price, and quality of energy supply, and psychological factors. Among the primary identified psychological factors, there are perceptions of fairness (both distributive and procedural; Walker & Devine-Wright, 2008; Wolskin, 2007), place-attachment and place-identity, trust, and values (respectively; Devine-Wright, 2005, 2009; Montijn-Dorgelo & Midden, 2008; Bidwell, 2013).

Regarding mitigation technologies, recent studies have examined specific technologies and/or variables to understand how various factors impact the social acceptance of SETs. In particular, several recent studies have explored the role of procedural variables, such as trust and fairness. Regarding trust, perceiving decision-makers involved in the energy initiatives as reliable, and feeling onself as included in the decision-making processes (Međugorac &

Schuitema, 2023), appears to be crucial for individuals to engage in pro-environmental behaviors – both in mitigation and adaptation efforts (see Cologna & Siegrist, 2020) – particularly in fostering public support for energy policies and promoting the adoption of sustainable technologies (Liu et al., 2019). Furthermore, it has been shown that integrity-based trust, compared to competence-based trust (Palomo-Vélez et al., 2024), is crucial in encouraging public support for transitioning from fossil fuels towards sustainable energy. Regarding fairness, studies like those by Sonnberger and Ruddat (2017) have shown that it directly impacts the acceptance of these technologies and that trust in decision-makers may have varying impacts on acceptance depending on the “type” of considered decision-maker. Liu et al. (2021) proposed that trust and fairness are involved in the social acceptance process but at different levels. They hypothesized that trust affects how technologies are perceived as either beneficial or risky, while fairness influences how these perceptions affect the acceptance of the technologies. Other research has focused on the emotional sphere (Cousse, 2021; Cousse et al., 2020; Cousse et al., 2021), highlighting the critical role emotions play in the acceptance process. These researches draw attention to the importance of affective variables, which – like cognitive ones – can significantly impact the acceptance of SETs (see also Cass & Walker, 2009; Perlaviciute, Steg, et al., 2018). Specifically, Cousse et al. (2020) showed that those who strongly oppose technologies (in that case, wind energy) often report negative or ambivalent emotional states. Another line of research has focused on individuals' values and morality and their central role in driving pro-environmental behaviors (see Steg et al., 2014), particularly the acceptance of such technologies (e.g., Perlaviciute & Steg, 2015). These studies suggest that values impact choices and preferences for energy technologies and that the salience of specific values (e.g., biospheric *vs*. egoistic) can lead to a preference for (respectively) alternatives to traditional (fossil) energy sources. A recent Bidwell (2023) study also found that values impact acceptance and beliefs about energy technologies. Regarding the moral sphere of individuals, several studies have highlighted its central role in acceptance processes. For instance, Scovell (2022), in a critical review of the antecedents of social acceptance of hydrogen energy, emphasizes that while few studies have explored the relationship between personal (moral) norms and the social acceptance of this technology, those have reported significant and substantial effects. Moreover, by integrating various behavioral theories, several studies have identified social influence (conceptualized as social norms) as one of the main levers for accepting these technologies (e.g., Wolske et al., 2017). Recent studies have further shown that social norms predict support for energy transitions and sustainable energy sources and that this relationship is influenced by cultural and contextual factors (e.g., Chan et al., 2022; Curtius et al., 2018).

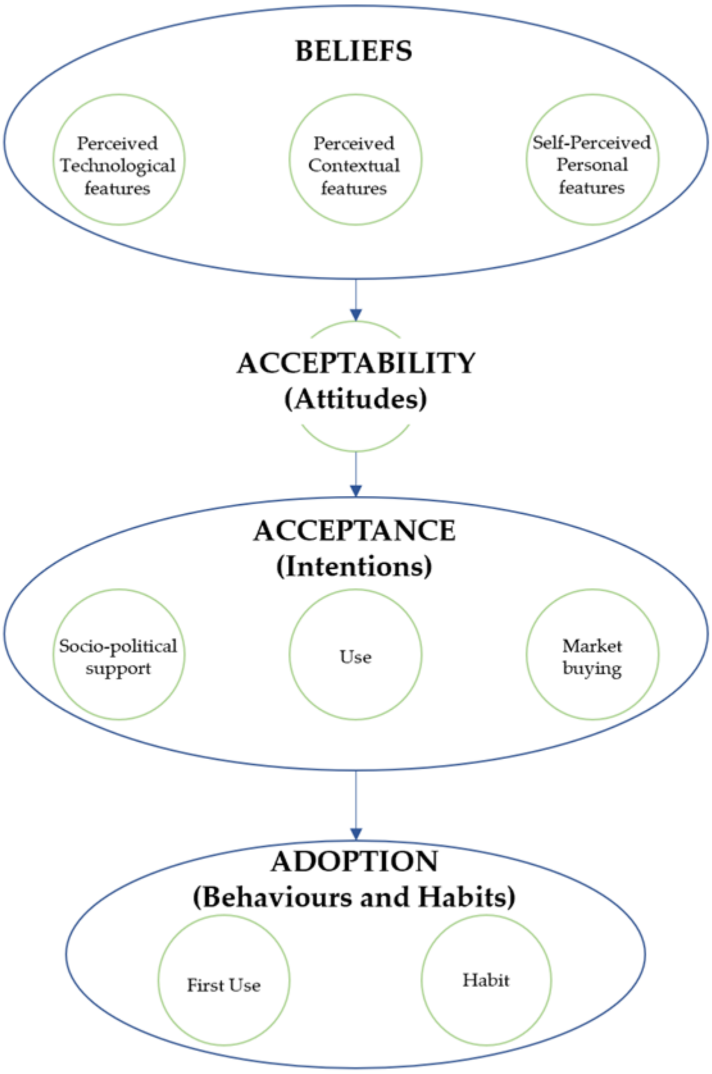
Regarding adaptation technologies, fewer social-psychological studies exist, and they are primarily exploratory (e.g., Low et al., 2022), aiming to investigate individual and expert opinions – given the public's limited awareness – through mainly qualitative analysis techniques (Low et al., 2022; Low et al., 2024). These and other studies (e.g., Sovacool, Baum, & Low, 2022b) highlight the necessity for public engagement and inclusive governance in developing and disseminating adaptation technologies (e.g, geoengineering), raising concerns about their high energy consumption and socio-political equity. Both the experts and the general public emphasize the importance of justice, transparency, and trust in the institutions managing these technologies, stressing the need for systemic adaptation efforts (such as decarbonization) alongside mitigation to address the root causes of climate change. Nasi et al. (2023) further emphasize the importance of promoting more proactive and transformative adaptation efforts, introducing the concept of transilience. Unlike resilience, which focuses on recovery, transilience encompasses three dimensions: persistence, adaptability, and transformability, capturing individuals' perceived ability not only to withstand climate risks but also to positively transform and seize new opportunities through adaptation. Additionally, through a cross-cultural approach, Low et al. (2024) begin to explore potential disparities in perceptions between the “Global South” and the “Global North” regarding adaptation technologies. Using a cross-cultural and quantitative approach, Contzen et al. (2024) investigate differences in perceptions across countries with different cultural and economic realities. Their study shows that participants from the “Global South” exhibit higher acceptance of such technologies (in that case Solar Radiation Management, SRM), likely due to their greater vulnerability to climate change. Moreover, despite the general acceptance of SRM, many expressed concerns about its ethical implications, potential side effects, and the fact that it does not address the root causes of climate change. The study also identifies the technology’s perceived effectiveness and perceived negative impacts as variables that seem to predict SRM acceptance.

Unfortunately, there are relatively few studies that have compared mitigation technologies with adaptation or negative emissions technologies (e.g., Ashworth et al., 2019; Moynihan & Schuitema, 2020), which highlight both substantial similarities in the processes of social acceptance, and crucial differences due to the adoption context and specific characteristics and perceptions of the technology itself.

Finally, several review articles and meta-analyses have focused on single specific technologies (e.g., solar; Schulte et al., 2022), revealing different facets of their social acceptance, often linked to the intrinsic characteristics of the technologies themselves.

More recently, in an attempt to systematize the process that drives widespread acceptance of both types of technologies and drawing from classical theories (such as the value-belief-norm theory, VBN; Stern et al., 1995), the study by Bonaiuto and colleagues (2024) identifies individual beliefs as the primary specific antecedent of the social acceptance process for sustainable energy technologies. Specifically, the study categorizes these technological social acceptance process specific beliefs into three main clusters – beliefs related to the technology being adopted, to the adoption context, and to the adopting person – within which the variables described and analyzed in the literature so far are grouped. The study hypothesizes that beliefs from all these three clusters can trigger the social acceptance process by first promoting the acceptability of the technologies, subsequently leading to their acceptance, and finally to their adoption (see Figure 2).

Figure 2 – *Beliefs–based social acceptance process.*



Source: *Bonaiuto et al. (2024).*

1.3. Norms, Emotions, and Pro-environmental Behaviors

Since the early modern psychological experiments on social influence (see Asch's conformity experiment; Asch, 1951), it has been well-established that people's opinions and behaviors are strongly influenced by those around them. Classical research (e.g., Festinger, 1954) further corroborates this hypothesis through numerous empirical findings.

This social influence, with the theorization of the Focus Theory of Normative Conduct (TNC, Cialdini et al., 1990, 1991), has been conceptualized and studied as a normative influence, distinguishing between two different types of norms – what others approve (injunctive norms) and what others do (descriptive norms) – responding to different motivations (Cialdini et al., 1990, 1991; Thøgersen, 2006). Building on the TNC, psychological studies have strongly confirmed the significant role of normative beliefs in shaping PEBs (Bamberg & Möser, 2007; Cialdini & Jacobson, 2021; Schultz, 2022; Thøgersen, 2006), showing how people assess their behavior by comparing it with what others do (or refrain from doing) and with what others approve (Cialdini et al., 1991; Cialdini & Jacobson, 2021; Nolan, 2021; Schultz et al., 2007). Research indicates that PEBs can be effectively encouraged when individuals realize that their behavior is less eco-friendly than that of their peers (Nolan et al., 2008; Schultz, 2022). Additionally, social comparison (framed as social norms) has proven to be a more effective strategy for promoting PEBs than approaches like education or feedback (Bergquist et al., 2023; Constantino et al., 2022). In particular, several articles (e.g., Gifford & Nilsson, 2014; Schultz et al., 2007) have emphasized the central role of the interaction between injunctive and descriptive social norms, highlighting their reinforcing effects (Allcott, 2011; Bonan et al, 2020; Schultz et al., 2007) and identifying conditional effects of conflicting norms (Gifford & Nilsson, 2014; McDonald et al., 2013).

In addition to the numerous correlational or experimental empirical findings just mentioned, Abrahamse and Steg (2013), Geiger et al. (2019), and Bergquist and colleagues (2019) provided important meta-analytic evidence of the impact of social norms on PEBs. The studies demonstrated, through the analysis of numerous experiments, that social norms directly and significantly affect PEBs. Bergquist and colleagues (2019) also found that implicitly induced social norms have a greater effect on PEBs than explicitly induced ones and that social norms tend to be more influential in individualistic countries than in collectivist ones, contrary to the findings of research on tightness-looseness (see Gelfand et al., 2006; Gelfand et al., 2011), which hypothesized and demonstrated that norms have a greater impact in collectivist (tighter) contexts.

On the other hand, several studies have highlighted that while the role of norms in promoting PEBs is central, their effectiveness depends on the context in which they are applied and the specific motivations driving individuals to follow them (e.g., Perry et al., 2021). The authors then emphasize the importance of evaluating in which situations normative influence should be used to promote PEBs and, more importantly, what type of PEBs.

Moreover, although the role of social norms in influencing PEBs is widely discussed in the literature, and although research on normative influence has often focused on the motivational characteristics that lead social norms to impact attitudes, intentions, and behaviors (Cialdini et al., 1991; te Velde & Louis, 2022), a recent review (Wolske et al., 2020) highlighted that much remains to be studied about the motivations that lead normative influence and social comparison to alter people's PEBs. Similarly, a subsequent review (Schultz, 2022) emphasized the need to identify which factors mediate or moderate the relationship between social norms and behavior, suggesting several socio-psychological levers that could be activated to enhance the effectiveness of social comparison in promoting pro-environmental behaviors.

Packard and Schultz (2023) suggested that social comparisons would report emotional and motivational effects. Thus, it may be the emotions felt as a result of social comparison that convey and reinforce the effect of norms. Behaving “worse” than others toward the environment would elicit negative emotions (e.g., shame), decreased self-esteem, and even guilt (Diel & Friese, 2024). This type of comparison would also promote a motivational drive to modify personal behaviors in order to restore one’s own social status (de Hooge et al., 2010). Conversely, behaving “better” than others toward the environment would elicit positive emotions (e.g., pride) and increase self-esteem (Diel, Grelle, & Hofmann, 2021; Wood, 1989), motivating people to continue to act pro-environmentally (Schneider et al., 2017). However, in some cases, people’s motivation to improve might dampen, causing PEBs to decrease (Diel, Broeker, et al., 2021; Diel, Grelle, & Hofmann, 2021). In fact, the satisfaction triggered by social comparison and such a positive emotional state, generating behavioral deactivation (Lazarus, 1991), and making additional information processing unnecessary, could increase the likelihood of future compliance (te Velde & Louis, 2022), leading to decreased PEBs. It is also known in the literature (Schultz et al., 2007) how knowing to behave “better” than others toward the environment – if not accompanied by social approval – decreases previously implemented PEBs.

Moreover, despite the strong and consistent impact that descriptive norms have on PEBs, we know relatively little about how descriptive norms make us feel. Unlike personal norms and injunctive social norms – the impact of which, on the emotional component and particularly on emotions such as pride or shame, is known (e.g., Fessler, 2007; Suhay, 2015) – it is, in fact, not yet clear what kind of emotional response may arise from descriptive social norms. Among the few studies that have investigated the impact of descriptive norms on people’s emotional responses, a study by Vesely and colleagues (2022) examined the emotional reactions related to the behavior performed after receiving normative feedback but not the emotional response to the normative feedback itself. Similarly, Bissing-Olson and colleagues (2016), highlighting the impact of PEBs on feelings of pride, examined how descriptive norm can moderate the relationship between PEBs and emotional responses to those behaviors. However, their study did not explore emotional reactions to the norm itself.

Packard and Schultz (2023) have tried to advance some hypotheses in this regard, suggesting that descriptive norms, by not eliciting immediate social approval or disapproval (Cialdini et al., 1991), might lead to low arousal emotional responses or neutral valence emotions. These emotions triggered by descriptive social norms, according to the authors, could still drive behavior just as high-arousal emotions triggered by injunctive social norms.

Moreover, as highlighted by Diel and Friese (2024), people would prefer to compare themselves, regarding environmental issues, with others who behave less pro-environmentally than they do. This, by promoting positive emotions, would give people social value (Diel, Grelle, & Hofmann, 2021). However, as previously anticipated, even though most research in the literature considers experiencing positive emotions following a pro-environmental action to be a lever for promoting the perpetuation of PEBs (Onwezen et al., 2014; Schneider et al., 2017), it still make sense to assume that only perceiving negative emotions leads to subsequent enactment of PEBs. According to the mobilization-minimization hypothesis (Taylor, 1991), indeed, negative experiences would evoke strong cognitive responses that mobilize people to minimize the impact of the experience. This pattern, being significant predominantly for negative experiences (as opposed to positive and neutral experiences), is likely to guide people to try to counter negative information about themselves by generating counterarguments and counter behaviors to refute them (Fransen et al., 2015). On the other hand, although much previous research has hypothesized a reinforcing effect of PEBs by positive emotions, these hypotheses have often been disconfirmed (e.g., Mallett et al., 2013).

Therefore, as initially anticipated, such emotional response would convey and reinforce the effect of these social norms, but without changing the direction of the effect. In fact, as found in the study by Schultz et al. (2007), knowing that one behaves more pro-environmentally than others would decrease commitment to pro-environmental issues, leading to phenomena such as the magnetic middle (Schultz, 2022). By eliciting positive emotions, this would not change the effect of such social norms, which instead should be more influenced by morality (i.e., moral norms; Wonneberger, 2018) and the value sphere of individuals (Steg et al., 2014).

1.4. Social comparison as a leverage for social acceptance

Considering the role of social norms as analyzed in the literature, the impact of social influence in promoting a wide range of PEBs is central (see Cialdini & Jacobson, 2021). Moreover, numerous studies have highlighted that it is often easier and more cost-effective to manipulate and influence the context to impact individuals rather than directly targeting individuals themselves (e.g., De Groot et al., 2021). For this reason, studying the impact of social norms is not only theoretically significant but also practically valuable, given the relative ease with which attitudes, intentions, and/or behaviors can be influenced through normative messaging (e.g., Schultz et al., 2008). Cialdini and Goldstein (2004) further emphasized that social norms are among the most powerful tools for persuasion. Due to their broad applicability, they can serve as a specific lever for enhancing the social acceptance of SETs and can also shape and influence various phenomena that indirectly affect the acceptance of such technologies, such as trust in decision-makers (see Bicchieri et al., 2011; Krueger et al., 2008; Oyebode & Nicholls, 2023, for a review on the relationship between social norms and trust).

Numerous studies have indeed demonstrated that these norms have a specific impact on behaviors closely related to the social acceptance of sustainable technologies, such as energy conservation (Abrahamse et al., 2007; Bonan et al., 2020; Fornara et al., 2016) and support for specific environmental and energy policies (e.g., De Groot & Schuitema, 2012).

For instance, the study by De Groot and Schuitema (2012) demonstrated that environmental policies supported by the majority of the population are perceived as more acceptable. The study further highlights how social norms are closely intertwined with the social and political context in influencing pro-environmental decisions and choices, showing that social influence can lead to the acceptance of more coercive environmental policies.

Regarding the impact of social influence on energy conservation, several studies have shown that providing normative feedback leads to more responsible and sustainable energy consumption (Schultz et al., 2007; Allcott, 2011). In particular, Allcott’s (2011) research provided empirical evidence from a large sample of American citizens, demonstrating that mailing social comparisons to residential energy users reduces their energy consumption.

Given the intrinsic nature of these behaviors, necessary for fostering a successful ecological transition, these studies have paved the way for numerous research efforts – especially in the last decade – investigating the role of social norms in influencing the social acceptance of sustainable technologies (e.g., Barth et al., 2016), and more specifically, SETs (e.g., Abreu et al., 2019).

Numerous studies have investigated the impact of injunctive and descriptive social norms on the social acceptance of various SETs. Given the higher TRL and widespread adoption of solar energy (especially photovoltaics), research on social norms, particularly descriptive norms, has predominantly focused on this energy technology. Bollinger and Gillingham (2012) were the first to examine the role of social influence (considered as descriptive social norms) in adopting photovoltaic panels. Following their work, several researchers have demonstrated how injunctive norms (Halder et al., 2016; Li et al., 2022; Wolske et al., 2017), descriptive norms (Chen et al., 2016; Graziano & Gillingham, 2015; Müller & Rode, 2013; Rode & Weber, 2016), and their combination (e.g., Korcaj et al., 2015) are correlated to the adoption and/or support of different forms of solar energy. The study by Arroyo and Carrete

(2019) identified normative motivations (personal and social norms) as the primary driver for adopting photovoltaic panels, also highlighting the centrality of contextual variables (e.g., economic factors), as the socioeconomic status of participants moderates the relationship between norms and adoption. Moreover, Curtius et al. (2018) theorized that descriptive norms influence the perception of injunctive norms and that both can guide the intention to install photovoltaic panels, either directly or indirectly (in the case of descriptive norms). Finally, through a meta-analytic contribution, Schulte and colleagues (2022) confirmed the significant impact of social norms on the acceptance of solar energy.

A smaller body of research has analyzed the impact of social norms on the acceptance of other types of SETs. On a correlational level, studies by Irfan et al. (2021) and Chan et al. (2022) have reported a significant relationship between social norms and the social acceptance of SETs. On the other hand, Vesely and colleagues (2022) provided experimental evidence showing that descriptive social norms influence support for SETs, also highlighting the emotional impacts resulting from specific behaviors (such as monetary donations) carried out after receiving normative feedback. Furthermore, Zhou et al. (2019), using archival data, demonstrated that normative influence effects can also occur across nations. In their study, they analyzed several European countries and found that energy policy changes in neighboring countries perceived as culturally similar had influenced individual nations' policies over time. While this national and continental level evidence requires further exploration and a more detailed examination of specific historical and contextual factors, it suggests the central role of normative influence in promoting not only the local adoption of these technologies but also a broad, effective energy transition.

Finally, regarding adaptation technologies, few studies have investigated the effect of social norms on their acceptance. Considering the relationship between uncertainty and social norms described by Perry et al. (2021) and given the significant uncertainty surrounding the adoption of these technologies and their respective outcomes (Sovacool, Baum, & Low, 2022a), social norms can be expected to have a greater effect on the social acceptance of mitigation energy technologies than on adaptation energy technologies. However, the few studies that have examined the role of social norms in influencing the acceptance of adaptation technologies (such as negative emissions and geoengineering technologies; e.g., Klaus et al., 2020) have shown that social norms are the primary driver of acceptance.

Therefore, social norms, along with other previously mentioned variables (e.g., personal norms), can play a crucial role in promoting the acceptance and subsequent adoption of sustainable energy technologies. Social norms and social comparison should be considered key areas for further exploration, given their limited application to specific categories of SETs, and given the lack of understanding regarding factors that may promote or hinder the impact of social norms on PEBs (e.g., emotions; see paragraph 1.3). Despite the extensive literature on the impact of social norms on the acceptance of SETs, numerous questions still need to be answered, which this Thesis seeks to address. Firstly, given the near-total absence of studies examining the role of social norms on the acceptance of adaptation technologies, exploring this emerging area can provide initial empirical insights into the effect of social norms on the acceptance of little-known and experimental technologies. This would also offer practical guidance for designing persuasive normative messages to facilitate the adoption of new technologies, products, and services.

While it is well established – starting from the Elaboration Likelihood Model (ELM; Petty & Cacioppo, 1986) – that the impact of external factors (peripheral cues) such as social norms is more substantial among individuals with limited prior knowledge and weak pre-existing attitudes, comparing the influence of social norms across various technologies and technology categories (i.e., mitigation *vs*. adaptation technologies) offers an opportunity to test these theoretical foundations. Such comparisons may either validate or challenge the theoretical assumptions that social norms should influence more adaptation technologies (less known) rather than mitigation technologies, prompting discussions on the differential effects of social norms on different types of SETs.

Lastly, although several studies have investigated the relationship between social norms and emotional responses in guiding PEBs (see paragraph 1.3), more research is needed to explore this connection in the context of SETs acceptance. This Thesis aims to enrich the sparse literature on emotional responses to descriptive norms in the realm of PEBs, and to identify how norms and emotions interact and how norms can trigger emotional responses within the broader decision-making and behavioral processes that drive individuals to support and adopt SETs.

In summary, while the influence of social norms on the social acceptance of SETs has been extensively discussed in the literature, there remains a lack of clarity regarding what drives individuals to adhere (or not) to these norms, as well as when and for which technologies these norms have a significant impact.

CHAPTER 2

Study 1[1]

2.1 Aim of the study

Considering the fundamental importance and growing interest in the social acceptance of SETs, Study 1 is a meta-analytic, exploratory study that addresses three critical gaps identified in existing literature.

1. A lack of meta-analyses that explore the phenomenon of social acceptance of various renewable and sustainable energy technologies: existing meta-analyses focus on a single technology, such as solar energy (Schulte et al., 2022) or may not specifically address energy technologies but rather sustainable technologies in general (Neves et al., 2022).
2. Research in psychology on the acceptability and acceptance of SETs - as a relatively young field of study - is still underdeveloped compared with other areas of environmental psychology. This implies that there are still many theoretical perspectives that have not yet been tested in this area.
3. There are very few studies that investigate the acceptability and acceptance of adaptation or “negative emission” energy technologies (e.g., solar radiation management or bioenergy with carbon capture and storage).

The study aims to bridge these gaps by setting several objectives that provide an integrated and comprehensive understanding of the extensive but fragmented literature through a

[1] This chapter is based on a previously published paper: Milani, A., Dessi, F., & Bonaiuto, M. (2024). A meta-analysis on the drivers and barriers to the social acceptance of renewable and sustainable energy technologies. *Energy Research & Social Science*, 114, 103624. The content has been adapted for incorporation into this thesis.

thorough quantitative synthesis that identifies the critical predictors of the acceptability and acceptance of SETs.

First, analyzing the effects of numerous antecedents of social acceptance of different energy technologies highlights which variables have been studied and which have not concerned the topic of social acceptance of SETs. Highlighting which variables (and how often) have been investigated, the outcome can clarify the research theoretical framework on a large scale. Finally, by classifying the effects of these variables on social acceptability and acceptance, it is possible to promote future research to investigate the effect of the less studied variables with a greater effect on social acceptance.

On the other hand, the choice to analyze a large number of technologies also leads to an advancement of the state of the art. Several studies (e.g., Visschers & Siegrist, 2014) highlighted the differences in the factors that drive (or hinder) the social acceptance of various energy technologies, and others highlighted how our perception of these technologies as adhering to our identity and values (e.g., Palomo-Vélez et al., 2021) can influence their acceptance and/or how other factors can influence acceptance itself. Therefore, the investigation of many technologies - even though it risks increasing heterogeneity and decreasing the generalizability of the results - allows for a comparison between different technologies through moderation analyses (Hedges & Pigott, 2004). By highlighting similarities and/or differences in the social acceptance of these technologies, the study aims to uncover the general factors that can lead to widespread acceptance across various energy technologies, highlighting, on the other hand, the specific factors that can be leveraged to promote individual technologies more effectively.

Finally, given the growing interest in adaptation technologies, it becomes crucial to understand whether using the promotion techniques that have been used so far for mitigation technologies can work for them as well, or whether they would rather need to be customized to the new contexts.

2.2 Method

In line with recommendations from the literature (Card, 2015; Haddaway et al., 2015), two sets of meta-analyses have been performed. The first focused on acceptability, while the second centered on the acceptance of sustainable and renewable, mitigation and adaptation, energy technologies. To ensure standardized reporting, the guidelines outlined in the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) were adhered (Moher et al., 2009; Page et al., 2021).

2.2.1 Literature search

Three steps were taken to conduct the literature search. Pertinent articles (i.e., articles by the most relevant authors in the field) were consulted first. These were searched on the Google Scholar database, using relevant keywords (e.g., "social acceptance" and "energy technologies"). Given the vast number of studies, publications by authors with extensive experience in the field, and articles published in prestigious journals recognized by the scientific community were considered. The acceptance of particular SETs was also examined in reviews and meta-analyses (e.g., Neves et al., 2022). Finally, keywords associated with the acceptability or acceptance of SETs were combined to search the literature in the databases Web of Science, PsycINFO, and Scopus. On 13th October 2022, a database search was first carried out. Then, on 22nd February 2023, a follow-up search was done to add to the meta-analyses the articles that were published during that period.

The search string used consists of three levels which correspond to the dependent variables (DVs) of the study (acceptability and acceptance), the most widely researched antecedent (independent variables; IVs) of acceptability and acceptance of SETs that were chosen after conducting a literature review (e.g., Huijts et al., 2012), and the mitigation and adaptation energy technologies investigated.

The three levels are presented below:

“acceptability” OR “attitude” OR “acceptance” OR “intention to buy” OR “intention to support” OR “intention to use” OR “social support” OR “opposition” OR “adoption”

AND

“Technology feature” OR “Contextual factor*” OR “Economic aspect*” OR “market aspect*” OR “Policy aspect*” OR “Social-psychological factor*” OR “Knowledge” OR “Experience” OR “outcome efficacy” OR “Value*” OR “Emotion*” OR “Trust” OR “Norm*” OR “Fairness” OR “Place attachment” OR “place identit*” OR “environmental identit*”*

AND

“solar energ” OR “Solar Thermodynamic” OR “Solar fuel*” OR “wind energ*” OR “Geothermal” OR “hydroelectric energ*” OR “biofuel*” OR “biomass energ*” OR “marine current*” OR “ocean energ*” OR “tidal” OR “thermoelectric technolog*” OR “thermochemical conversion” OR “electrolytic hydrogen” OR “Soil carbon sequestration” OR “Biochar” OR “carbon capture and storage” OR “Ocean alkalinization” OR “Ocean fertilization” OR “Direct air capture and storage” OR “Carbon capture utilization and storage” OR “Stratospheric Aerosol*” OR “Space-Based Reflector*” OR “Cloud Brightening” OR “albedo change” OR “Albedo Management” OR “Cloud Thinning” OR “geoengineering” OR “climate engineering” OR “Ice protection” OR “High altitude sunshade*”*

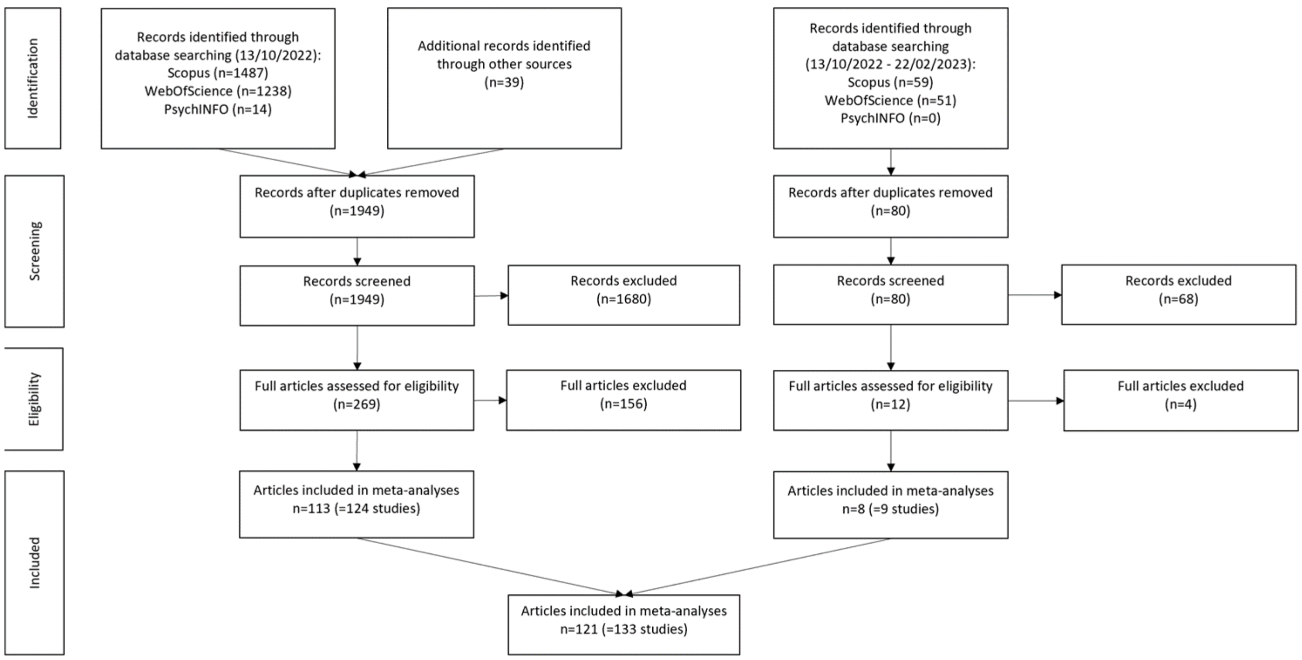
Energy technologies were selected from previous studies (see De Luca et al., 2020) and from an examination of the IPCC report (2022), focusing on widely studied options, clustering them by mitigation/adaptation and TRL.

Sustainable technologies such as electric cars and smart grids were then excluded because they have an “indirect impact on the environment”, that is, they are sustainable because they use sustainable energy or optimize consumption. Finally, nuclear energy was eliminated because of biases related to previous historical events, making it difficult a comparison with the other technologies (Kim, 2013; Verplanken, 1989).

Finally, an attempt was made to balance mitigation and adaptation technologies, considering their TRL.

The search process led to the collection of 2888 articles. After selection, 121 articles were considered, with a total of 133 studies. The selection process is shown in the PRISMA diagram, presented in Figure 3.

Figure 3 - *PRISMA Flow Chart*



2.2.2 Inclusion criteria and selection of studies

Studies were considered if they satisfied the following requirements.

The articles' whole texts had to first be located (and accessible) online in scientific databases. The authors of articles whose full texts could not be located were personally asked for the articles' full texts. A total of 8 out of the 15 requested articles were received, with a response percentage of 53.3 %. Following that, studies were required to present quantitative data on the acceptability and acceptance of SETs. The meta-analyses also included studies that did not specifically mention technology but instead, for instance, discussed renewable and sustainable energy technologies generally.

Additionally, studies had to report specific statistical coefficients to express the association between the IVs and acceptability or acceptance, such as Pearson's *r*, standardized regression coefficients, Odds Ratio, or others. Authors were individually contacted and requested to give the requisite statistics or dataset if studies described pertinent data but did not provide them. A total of 62 authors were contacted personally; 7 responded (response rate: 11.3 %) and gave data or statistics for the meta-analyses.

When longitudinal studies were examined, T0 (first data collection, before the intervention) was considered, unless the specific change between study times or the specific intervention/manipulation was of interest. Even regarding longitudinal studies without intervention, the first measurement was considered so as not to encounter problems related to sample independence or incorrect effect estimates. In the case of experimental studies, unless it made sense for the research to select data from the experimental group, the data from the control group were considered.

Finally, the articles had to be written in English to be included in the meta-analyses.

2.2.3 Analysis strategy

Following the guidelines of Hornsey et al. (2016), meta-analyses were conducted for variables that were analyzed in a minimum of five studies.

Effect sizes were derived using the following procedures. If studies provided multiple effect sizes per sample, these were consolidated into a single summary effect size per study by calculating the average effect sizes (Borenstein et al., 2021). For example, if a study examined the acceptability or acceptance of two distinct energy technologies, two correlations would be obtained for each IV. However, including these correlations separately would violate the meta-analytical assumption of independent data. Therefore, before inclusion in the meta-analysis, effect sizes from the same study were summarized. This strategy is employed in articles (and specifically in other meta-analyses) that evaluate multiple effect sizes (Van Valkengoed & Steg, 2019).

The minimum sample size was applied when sample sizes varied across studies due to missing data or lack of information. Then, effect sizes from studies using reverse-coded questions (e.g., low score = high social acceptability/acceptance) were reversed. Subsequently, all effect sizes were transformed into Pearson's *r*. The formula by Rupinski and Dunlap (1996) was utilized to convert Spearman's rho (*rs*) to Pearson's *r*, the formula by Peterson and Brown (2005) was employed to convert standardized regression coefficients (β), and the formula by Walker (2003) was utilized for converting Kendall's tau (τ). Finally, a variance-stabilizing transformation (and back transformation) to Fisher's z (*rz*) (and back to Pearson's *r*) was applied to all correlation coefficients using the Fisher's *z* formula by Borenstein et al. (2021) and the inverse of Fisher's *z* formula, respectively.

As standardized coefficients from regression models with covariates can differ from correlations, particularly when predictors in the models are highly correlated, caution was exercised when incorporating regression coefficients into the meta-analyses (Aloe, 2015).

Consequently, authors were contacted directly to request Pearson's *r* correlations whenever possible.

All analyses were performed using R (version 4.1.3) with the "metafor" package (version 3.8.1) (Viechtbauer, 2010). Random-effects meta-analysis models were applied for each factor.

2.2.4 Variables coding, merger, and relationships

The variables of interest, both independents and dependents, were gathered from the selected articles. Nevertheless, it was noted that multiple variables exhibited similar meanings, albeit being described differently. As a result, these variables were combined or fused considering their respective definitions and names. This consolidation process enhances the accuracy of the meta-analysis. For comprehensive details regarding the merged variables and their corresponding codifications, please consult Table 1A in Appendix A.

Specifically, the variables were coded to fit within the definition of the constructs under consideration, as listed in the introduction regarding DVs, and as listed below regarding IVs.

"Perceived benefits" refer to the perception of economic, social, environmental, and health benefits related to the specific technology (Huijts et al., 2012). "Emotional response" refers to the emotions elicited using a technology, or the perception of its risks and benefits (Cousse 2021; Cousse et al., 2020). "Fairness" is regarded as the perceived fairness of the process of technology development, adoption, and diffusion (Gölz & Wedderhoff, 2018; Liu et al., 2020a). "Trust in decision makers" is regarded as the competence and/or integrity of such decision makers (Liu et al., 2020b) (or as a general measure of trust). "Perception of human impact on climate change" refers to the anthropogenic responsibility for climate change (Ashworth et al., 2019). "Climate change concern" refers to people's concern about climate change and its consequences (Schultz, 2001). "Place attachment" includes a sentimental connection between people and the areas they frequently visit or live in (Devine-Wright, 2009). “Subjective knowledge” refers to perceived knowledge toward technology (Raju et al., 1995). “Government initiatives” refer to government measures (e.g., subsidies) in favor of technologies (Goldthau & Sovacool, 2012). “Perceived ease of use” refers to the ease of use of technology (Masukujjaman et al., 2021). “Social norms” refer to the implicit social rules that govern behavior within a community, guiding individuals on what is considered as the acceptable and appropriate conduct in various situations; these norms shape interactions and expectations, fostering social cohesion and order by promoting conformity to shared standards and values; while descriptive norms reflect what people actually do, providing a benchmark for typical actions, injunctive norms reflect what people believe is approved or disapproved, guiding behavior through perceived social expectations (Schultz et al., 2007). “Consumer innovativeness” is the participants’ propensity to innovate (Wolske et al., 2017). “Perceived behavioral control” refers to the perception of whether people can enact a particular action, considering their evaluation of the resources, opportunities, and challenges they expect to encounter; this concept mirrors individuals’ confidence in executing the intended behavior, thus shaping their intentions and subsequent actions (Ajzen, 2002). “Personal norm” refers to individuals’ moral beliefs (De Groot et al., 2013); according to the norm-activation theory, personal norms are expectations that stem from integrated values and a duty to participate in specific behaviors reflecting the commitment to the same values (Schwartz, 1968, 1977). “Perceived technology reliability” refers to the reliability of technology as perceived to be mature, safe, or efficient (Yun & Lee, 2015). “Ecological lifestyle” refers to a sustainable and pro-environmental lifestyle (Klaus et al., 2020). Finally, “Perceived cost” refers to the perception of technology as economically, socially, and environmentally costly (Wolske et al., 2017).

2.2.5 Normality of distributions

One of the assumptions for meta-analysis is that the effect sizes are normally distributed (Kontopantelis & Reeves, 2012). To verify the normality assumption, in Tables 1 and 2, estimates of the Shapiro-Wilk Normality test (Shapiro & Wilk, 1965) are presented. There were three factors for which the Shapiro-Wilk test highlighted the non-normality of effects distribution: namely, "Age" ($W = .84$; $p < .001$) and "Perceived risks" ($W = .92$; $p < .05$) as predictors of acceptability and "Perceived risks" ($W = .81$; $p < .01$) as a predictor of acceptance. These variables reported a non-normal distribution of effects even after outliers were removed. Therefore, meta-analyses with these variables were not conducted.

Table 1 - *Shapiro-Wilk normality test for Acceptability determinants*

Factor	**Shapiro-Wilk normality test**
Perceived benefits	$W = .94$ ($P = .10$)
Positive emotional response	$W = .91$ ($P = .31$)
Fairness	$W = .85$ ($P = .07$)
Trust in decision makers	$W = .93$ ($P = .17$)
Perception of human impact on climate change	$W = .98$ ($P = .95$)
Climate change concern	$W = .96$ ($P = .76$)
Place attachment	$W = .96$ ($P = .83$)
Subjective knowledge	$W = .93$ ($P = .38$)
Income	$W = .94$ ($P = .34$)
Education	$W = .93$ ($P = .14$)
Woman	$W = .96$ ($P = .47$)
Age	$\mathbf{W = .84}$ **(** $\mathbf{P = .0005}$ **)**
Conservative	$W = .96$ ($P = .64$)
Perceived risks	$\mathbf{W = .92}$ **(** $\mathbf{P = .04}$ **)**
Negative emotional response	$W = .96$ ($P = .82$)

Table 2 - *Shapiro-Wilk normality test for Acceptance determinants*

Factor	Shapiro-Wilk normality test
Attitude	W = .93 (P = .06)
Government initiatives	W = .93 (P = .58)
Trust in decision makers	W = .94 (P = .61)
Perceived benefits	W = .98 (P = .71)
Perceived ease of use	W = .95 (P = .74)
Social norms	W = .97 (P = .37)
Consumer innovativeness	W = .91 (P = .37)
Perceived behavioral control	W = .95 (P = .32)
Climate change concern	W = .96 (P = .52)
Personal norm	W = .88 (P = .20)
Perceived technology reliability	W = .97 (P = .91)
Ecological lifestyle	W = .91 (P = .43)
Subjective knowledge	W = .98 (P = .87)
Woman	W = .98 (P = .95)
Education	W = .91 (P = .21)
Income	W = .91 (P = .33)
Perceived risks	**W = .81 (P = .007)**
Perceived cost	W = .93 (P = .14)

2.2.6 Heterogeneity analysis

The heterogeneity observed in meta-analyses can be attributed to two different types of variability: within-study and between-study variability, which represent the variation among the true effect sizes. To evaluate the heterogeneity among the studies, several statistical measures were employed, namely Q, τ^2, and I^2. Cochran's Q test follows a chi-square distribution and aids in determining the statistical significance of the observed heterogeneity. It should be noted that the Q statistic is dependent on the number of studies and cannot be directly compared across different meta-analyses (Ioannidis et al., 2007). Additionally, when the number of studies in the meta-analysis is small, the Q statistic may have limited power to detect heterogeneity among the studies (Borenstein et al., 2021). Therefore, are also presented the parameter τ^2, which estimates the standard deviation of the true effects across studies, and the I^2 statistic, which provides a quantitative measure of heterogeneity. The I^2 values are expressed as percentages indicating the proportion of total variation in the observed effect estimates that can be attributed to heterogeneity between studies (Higgins & Thompson, 2002).

2.2.7 Publication bias

Given the tendency for statistically significant results to be more readily published than non-significant ones, publication biases can influence meta-analyses and lead to inflated estimates (Card, 2015). Although there is no way to completely handle publication bias (Franco et al., 2014), an attempt has been made to capture its effect and minimize it.

To try to manage the effect of publication biases, "grey literature", such as book chapters or doctoral dissertations, was initially included in the meta-analyses. However, given the extremely small number of studies in this category, these were excluded from the analyses.

To assess publication bias, therefore, the presence of "asymmetry" in the effect sizes was examined by plotting the distribution of effect sizes and standard errors around the pooled estimated effects. Along with failsafe *N* tests (Rosenthal, 1979), the trim-and-fill method (Duval & Tweedie, 2000), and Egger's regression test of funnel plot asymmetry (Egger et al., 1997; Egger et al., 2011), which offers a statistical measure of skewness, asymmetry was also evaluated.

Only the funnel plot asymmetry test of "Perceived benefits" was significant when considering the meta-analyses using acceptability as the DV (see Table 3). The trim-and-fill method imputed data points for the three analyses "Climate change concern", "Income", and "Conservative". Two studies were imputed to each of the three variables. If the studies that were imputed were included, the effects for "Climate change concern" and "Income" would be stronger. On the other hand, the inclusion of the imputed studies would result in the effect being non-significant for the variable "Conservative". According to the failsafe *N* tests, a significant number of non-significant effects would be required for each element to make the total impact non-significant. In conclusion, there is little proof that publication bias affected the impact sizes found in the current analyses.

Table 3 - *Analysis of Publication Bias for Acceptability determinants*

Factor	**Asymmetry**	**Trim and fill**	**Adjusted effect**	**Failsafe *N***
Perceived benefits	**$\|Z\|=2.22$, $P=.03$**	No data points imputed	NA	36727
Positive emotional response	$\|Z\|=.06$, $P=.95$	No data points imputed	NA	3661
Fairness	$\|Z\|=.16$, $P=.88$	No data points imputed	NA	2267
Trust in decision makers	$\|Z\|=.23$, $P=.82$	No data points imputed	NA	6773
Perception of human impact on climate change	$\|Z\|=1.20$, $P=.23$	No data points imputed	NA	371
Climate change concern	$\|Z\|=1.18$, $P=.24$	**2 study imputed**	**$r=.18$, 95%*CI*[.10,.27]**	2290
Place attachment	$\|Z\|=.74$, $P=.46$	No data points imputed	NA	205
Subjective knowledge	$\|Z\|=.62$, $P=.53$	No data points imputed	NA	221
Income	$\|Z\|=1.54$, $P=.12$	**2 studies imputed**	**$r=.04$, 95%*CI*[.01,.08]**	176
Education	$\|Z\|=.14$, $P=.89$	No data points imputed	NA	NA (overall effect was already nonsignificant)

Woman	|Z|=1.17, P=.24	No data points imputed	NA	NA (overall effect was already nonsignificant)
Conservative	|Z|=.74, P=.46	**2 studies imputed**	***r*=-.03, 95%*CI*[-.07, .01]**	205
Negative emotional response	|Z|=.00, P=.99	No data points imputed	NA	453

Considering the meta-analyses with acceptance as the DV, the results indicate that only the funnel plot asymmetry tests for “Climate change concern” and “Ecological Lifestyle” were significant (see Table 4). Data points were imputed for four analyses using the trim-and-fill method; namely, “Climate change concern”, “Personal norm”, “Perceived technology reliability”, and “Income”. As for “Climate change concern” if the imputed studies were added, the effect would increase. On the other hand, concerning the variables “Personal norm” and “Income”, the inclusion of the imputed studies would lead to the non-significance of the effect. Finally, regarding “Perceived technology reliability” if the imputed studies were added, the effect would decrease. The failsafe *N* tests indicated only for the variable “Income” a non-substantial amount of non-significant effects would be needed to render the overall effect non-significant. This underlines the non-robustness of the effect of “Income” on acceptance.

Table 4 - *Analysis of Publication Bias for Acceptance determinants*

Factor	Asymmetry	Trim and fill	Adjusted effect	Failsafe *N*
Attitude	$\|Z\|$=1.80, *P*=.07	No data points imputed	NA	40047
Government initiatives	$\|Z\|$=.67, *P*=.50	No data points imputed	NA	1148
Trust in decision makers	$\|Z\|$=1.72, *P*=.09	No data points imputed	NA	2886
Perceived benefits	$\|Z\|$=1.68, *P*=.09	No data points imputed	NA	22726
Perceived ease of use	$\|Z\|$=.92, *P*=.36	No data points imputed	NA	967
Social norms	$\|Z\|$=1.55, *P*=.12	No data points imputed	NA	27714
Consumer innovativeness	$\|Z\|$=.84, *P*=.40	No data points imputed	NA	1074
Perceived behavioral control	$\|Z\|$=1.23, *P*=.22	No data points imputed	NA	12141
Climate change concern	**$\|Z\|$=2.05, *P*=.04**	**2 studies imputed**	***r*=.42, 95%*CI*[.32,.53]**	8731
Personal norm	$\|Z\|$=.89, *P*=.37	**1 study imputed**	***r*=.27, 95%*CI*[-.01,.55]**	695
Perceived technology reliability	$\|Z\|$=.81, *P*=.42	**1 study imputed**	***r*=.30, 95%*CI*[.18,.41]**	724
Ecological lifestyle	**$\|Z\|$=2.31, *P*=.02**	No data points imputed	NA	399

Subjective knowledge	$\|Z\|$=.67, P=.51	No data points imputed	NA	8343
Woman	$\|Z\|$=1.51, P=.13	No data points imputed	NA	59
Education	$\|Z\|$=.36, P=.72	No data points imputed	NA	NA (overall effect was already nonsignificant)
Income	$\|Z\|$=1.78, P=.08	**3 studies imputed**	***r*=.01, 95%*CI*[-.02,.05]**	**13**
Perceived cost	$\|Z\|$=.68, P=.50	No data points imputed	NA	6699

These results highlight how, despite the absence of excessive publication bias, the effects of some variables on the acceptability and acceptance of SETs are biased.

It is salient that in the field of energy research and social science, there is a tendency to overestimate the effect of “Perceived benefits” of technologies, while there is a tendency to underestimate the effect of “Climate change concern” in influencing the social acceptance of such technologies.

This could be influenced by the tendency, advanced by several research lines (such as NIMBY; Devine-Wright, 2005, 2009), to overestimate the centrality of self-centered (e.g., egoistic) values, which instead often influence pro-environmental behaviors only if supported by a value system centered on others and the environment (e.g., biospheric). In recent years, this approach has been criticized (Perlaviciute et al., 2021), promoting a biospheric interpretation of “energy” behaviors.

It then appears that the effect of political orientation (i.e., “Conservative”) and “Personal norm” is overestimated, again suggesting the need to investigate the impact of different value and identity framings in influencing energy behaviors.

2.2.8 Outlier analysis

In line with the recommended guidelines in meta-analysis (Viechtbauer & Cheung, 2010), outlier analyses were performed to assess the sensitivity of our findings and determine the extent to which individual studies influenced the conclusions. The outlier analyses employed various methods, including the "leave one out" approach (Sahebkar, 2013a; Sahebkar, 2013b), the 95th percentile method, and Cook's distances (Cook & Weisberg, 1982). Subsequently, the models were re-run without outliers to evaluate their impact (Viechtbauer & Cheung, 2010). Outliers were removed in 5 of the 30 conducted meta-analyses; namely, for "Income" and "Conservative" as acceptability determinants, and "Income", "Woman", and "Perceived Benefits" as acceptance determinants. Outliers were also identified in other meta-analyses, but they were removed from the analyses only if they had an impact on the normality of the distribution of effects or if they affected the significance of the results.

The study by Warren et al. (2014) and the study by Kim et al. (2019) were flagged as outliers in the meta-analysis examining the effects of "Income" on technology acceptability. The two studies emerged as outliers because they reported stronger than average negative and positive correlations, respectively. The removal of the two studies significantly changed the statistics related to the meta-analysis. Before the removal of the outliers, the analyses reported non-significant results ($r = 0.03$; $p = .07$; $I^2 = 87.79$), whereas, after their removal, the meta-analysis reported significant results ($r = 0.03$; $p < .05$; $I^2 = 78.29$) also reporting a clear reduction in heterogeneity between the effects of the individual studies (look at I^2 variance). In contrast, the removal of outliers did not impact the normality of the effect distribution, which was normal both before and after the removal of these studies ($W = .97$; $p = .87$ and $W = .94$; $p = .34$, respectively).

Two outlier studies were also identified in the meta-analysis that examined the effect of "Conservative" political orientation on acceptability. Specifically, the study by Whitmarsh et al. (2019) and the study by Bidwell (2023) were removed from the analyses. This is because the two studies reported anomalous results. First, the study by Whitmarsh et al. (2019) reported a positive effect due to being politically conservative about support toward CCS technologies, which is contrary to the literature and the other studies reviewed. Bidwell's study (2023), on the other hand, reported anomalous results as it reported a large negative correlation (Whitmarsh et al., 2019) - an effect that could be explained by the specificity of the sample analyzed - which deviated from the average effects of the other studies. Specifically, the results before the removal of the outliers reported non-significant results ($r = -.07$; $p = .06$; $I^2 = 97.69$) as well as a non-normal distribution of effects ($W = .79$; $p < .01$) while after their removal, the meta-analysis reported significant results ($r = -.05$; $p < .05$; $I^2 = 89.74$) distributed normally ($W = .96$; $p = .64$). In addition, removal of the outliers reported a clear reduction in heterogeneity between the effects of individual studies (look at I^2 variance).

Outliers were then also identified and subsequently removed in meta-analyses that investigated the relationship between the variables "Woman", "Income", and "Perceived benefits" and acceptance of energy technologies. Specifically, regarding the variable "Woman", the study by Oh et al. (2023) reported unexpected results, identifying a negative relationship between being a woman and the intention to accept (acceptance) such technologies. Although two other studies (Horne et al., 2021; Payen et al., 2022) also identified a negative relationship between these variables, they were not removed because the effect found did not differ substantially from the average effect of the other studies. In contrast, the removal of the study by Oh et al. (2023) significantly affected the results of the meta-analysis. Before the removal of that study, the meta-analysis reported non-significant results ($r = .06$; $p = .11$; $I^2 = 86.14$), whereas once the study was removed, the meta-analysis reported a significant relationship between gender and acceptance of these technologies ($r = .07$; $p < .05$; $I^2 = 82.60$). The removal of the study outlier did not impact the normality of the distribution of effects. Concerning the variable “Income”, studies by Gracia et al. (2018), Bashiri and Alizadeh (2018), and Arroyo and Carrete (2019) were identified as possible outliers. Indeed, the studies by Gracia et al. (2018) and Arroyo and Carrete (2019) reported a substantially larger positive relationship between perceived income and acceptance. The study by Bashiri and Alizadeh (2018) instead reported a negative relation between income and acceptance, not supported by the literature. The removal of these studies affected the results of the meta-analysis. Specifically, before the removal of the outliers, the relationship between “Income” and acceptance reported non-significant results (r = .06; p = .06; I^2 = 75.50), whereas, after the removal of these studies, the meta-analysis reported a significant relationship (r = .04; p < .05; I^2 = 5.81). Removal of the outlier studies did not impact the normality of the effect distribution but substantially effected the heterogeneity of effects, which after removal of these studies decreased noticeably. Finally, regarding the outliers that emerged from the meta-analysis that investigated the relationship between “Perceived benefits” and technology acceptance, the two studies in the article by Klaus et al. (2020) were identified as possible outliers. The two studies, indeed, reported a too strong relationship between “Perceived benefits” and acceptance. In particular, the two studies, one on geoengineering technologies and the other on CCS (Carbon Capture and Storage) technologies, reported two very large effects (Whitmarsh et al., 2019). Removal of these studies from the meta-analysis did not affect the significance of the relationship between the two variables before (r = .46; p < .001; I^2 = 97.61) and after removal of the outlier studies (r = .45; p < .001; I^2 = 95.87). In contrast, the removal of these studies impacted the normality of the effect distribution before (W = .93: p < .05) and after (W = .98: p = .71) the removal of the outliers, respectively.

2.3 Results

Meta-analyses were conducted on two total samples of 81,759 participants for acceptability and 31,806 for acceptance of SETs, for both mitigation and adaptation. 61 studies (53 articles) investigated acceptability, and 72 studies (68 articles) investigated acceptance. The total sample relating to acceptability, therefore, is significantly larger than the acceptance sample, although the total number of studies on acceptability is smaller than those on acceptance. This is probably due to the fact that acceptance research generally uses smaller sample sizes, a trend that could lead acceptance studies to less accurate results than acceptability studies. Regarding the geographical distribution of the studies' samples, 50 % of the studies that investigated technology acceptability were based in Europe, 29 % in North America, 13 % in Asia, 3.2 % in Africa, 3.2 % in Oceania, and 1.6 % in Central and South America. As for the studies that investigated technology acceptance, these had a different geographical distribution. Specifically, 61.3 % were Asian samples, 18.7 % European, 10.7 % North American, 4 % African, 4 % Oceanic, and 1.3 % Central and South American.

After preliminary analyses (see "Method"), effects were computed and ranked according to their size. For both the meta-analyses with dependent variable (DV) "acceptability" and those with DV "acceptance", the results emerging from the random-effect meta-analyses are shown below.

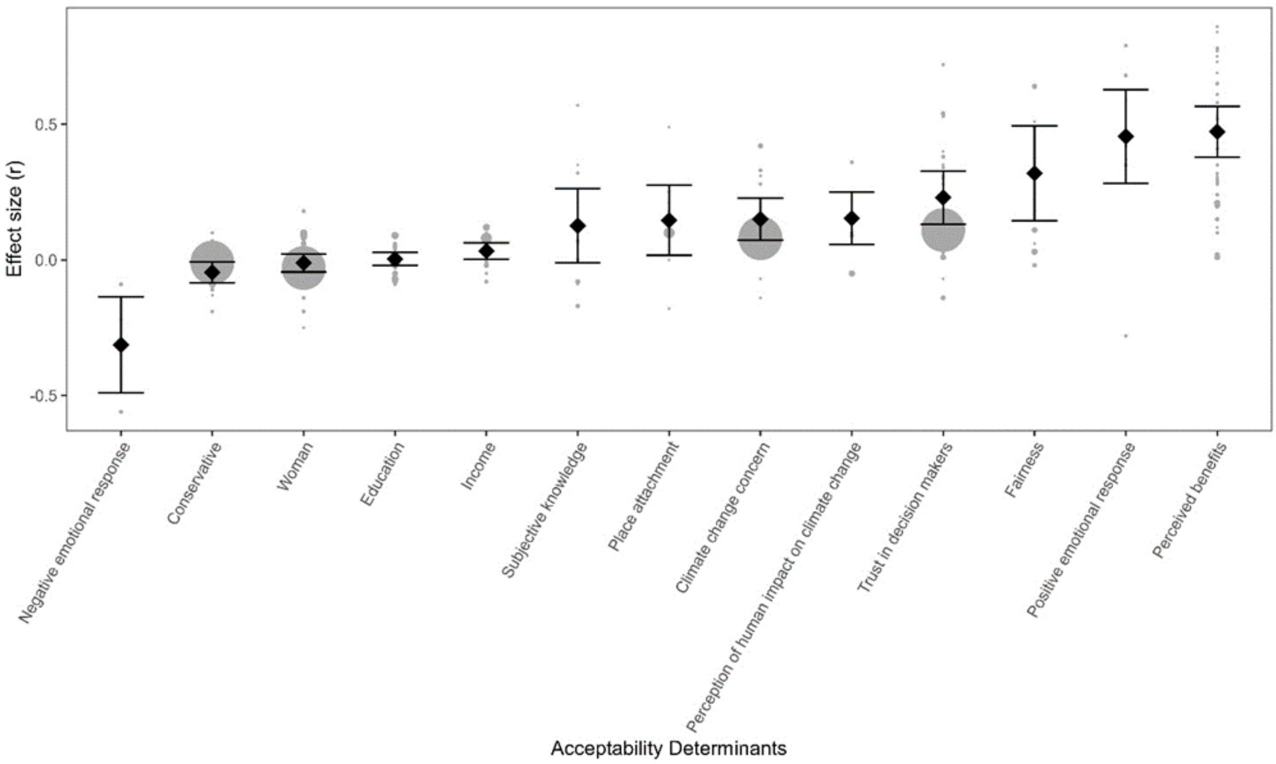
Table 5 shows the statistics highlighted by the meta-analyses on the acceptability of energy technologies, while in Figure 4 the effect sizes are ranked and shown graphically.

Table 5 - *Summary of estimated effects for the antecedents of acceptability*

Variable	*r*	95% CI	*k*	*n*	I^2	*Q*	τ^2	*P*
Perceived benefits	.47	.37 - .57	30	20709	98.83	2121.32	.126	<.0001
Positive emotional response	.46	.24 - .63	9	4854	98.64	729.57	.140	<.0001
Fairness	.32	.12 - .49	9	9145	98.95	881.43	.101	.002
Trust in decision makers	.23	.13 - .33	22	44007	98.78	1053.72	.062	<.0001
Perception of human impact on climate change	.15	.05 - .25	7	8817	95.38	142.49	.017	.002
Climate change concern	.15	.07 - .23	14	41419	97.47	333.11	.022	.0003
Place attachment	.15	.01 - .28	8	7594	94.54	52.32	.034	.03
Subjective knowledge	.13	-.02 - .26	11	7517	97.25	309.19	.054	.08
Income	.03	.003 - .06	17	22955	78.29	74.53	.003	.03
Education	.003	-.02 - .03	22	31452	77.03	96.65	.002	.79
Woman	-.01	-.04 - .02	27	63146	92.83	245.16	.007	.49
Conservative	-.05	-.08 - -.01	15	44009	89.74	82.26	.004	.03
Negative emotional response	-.31	-.47 - -.14	5	2707	95.23	145.55	.042	.0007

Note: *k represents the number of studies that have been included in the meta-analysis, n refers to the total number of participants across all the studies that have been included in the meta-analysis,* I^2 *denotes the proportion of heterogeneity attributed to differences between studies, Q represents the total heterogeneity observed in the analysis,* τ^2 *indicates the absolute heterogeneity between studies. The total number of studies in Table (k) exceeds the studies mentioned in the introduction because most studies are included in multiple analyses.*

Figure 4 - *Mean of estimated effects for the antecedents of acceptability*



Note*: Black diamonds are used to indicate the meta-analytical effect size (r) for each specific variable. Error bars surrounding the black diamonds represent the 95% confidence interval (CI) around the effect size. Grey circles represent the effect sizes observed in individual studies included in the meta-analysis, and the size of each circle corresponds to the sample size of the respective study.*

Mean correlational effect sizes were interpreted according to Cohen's guidelines (1992), whereby $r = .10$ represents a small, $r = .30$ a medium, and $r = .50$ a large effect. As shown in Table 5, the variables "Subjective Knowledge" ($r = .13$; $p = .08$), "Education" ($r = .003$; $p = .79$), and "Woman" ($r = -.01$; $p = .49$) have no significant effect on the acceptability toward SETs. Then, following Cohen's guidelines, it emerges that the variables "Conservative" ($r = -.05$; $p < .05$), "Income" ($r = .03$; $p < .05$), "Place attachment" ($r = .15$; $p < .05$), "Climate change concern" ($r = .15$; $p < .001$), "Perception of human impact on climate change" ($r = .15$; $p < .01$) and "Trust in decision makers" ($r = .23$; $p < .001$) have a small effect on the acceptability of energy technologies. On the other hand, the variables "Negative emotional response" ($r = -.31$; $p < .001$) and "Fairness" ($r = .32$; $p < .01$), "Positive emotional response" ($r = .46$; $p < .001$) and "Perceived benefits" ($r = .47$; $p < .001$) report a medium effect on acceptability.

As for the results of the meta-analyses regarding acceptance, these are given in Table 6.

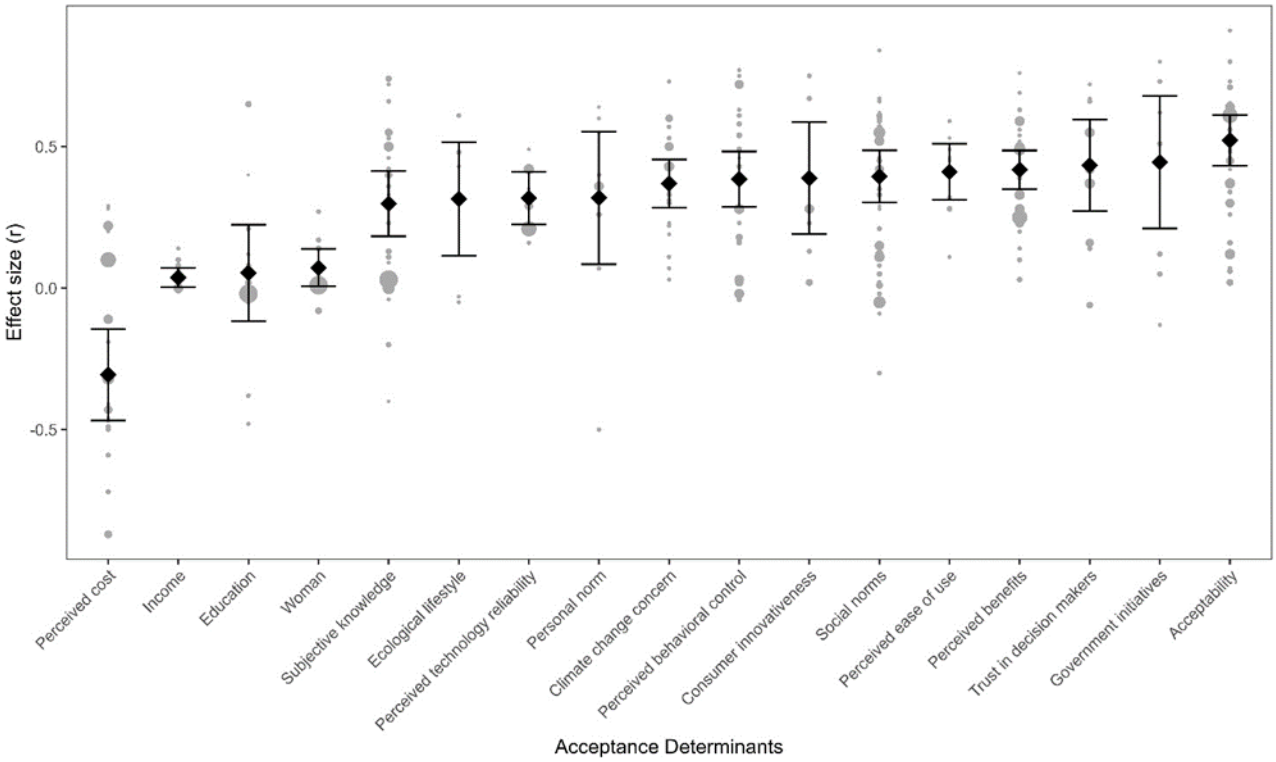
Table 6 - *Summary of estimated effects for the antecedents of acceptance*

Variable	r	95% CI	k	n	I^2	Q	τ^2	P
Acceptability	.52	.42 - .61	30	13453	98.33	1364.70	.135	<.0001
Government initiatives	.45	.13 - .68	7	2159	98.51	356.06	.218	.007
Trust in decision makers	.43	.24 - .59	9	5219	98.42	358.79	.112	<.0001
Perceived benefits	.42	.35 - .49	29	13377	95.87	524.91	.052	<.0001
Perceived ease of use	.41	.30 - .51	8	1862	86.63	50.19	.029	<.0001
Social norms	.39	.29 - .49	36	15555	98.05	1521.96	.119	<.0001
Consumer innovativeness	.39	.15 - .59	7	3029	98.06	281.05	.123	.002
Perceived behavioral control	.38	.28 - .48	25	10425	97.39	1038.62	.092	<.0001
Climate change concern	.37	.28 - .46	20	7815	95.10	296.05	.052	<.0001
Personal norm	.32	.04 - .55	8	2714	98.20	290.43	.174	.03
Perceived technology reliability	.32	.22 - .41	6	3968	89.51	46.83	.015	<.0001
Ecological lifestyle	.32	.08 - .52	6	1526	95.69	108.03	.090	.009
Subjective knowledge	.30	.17 - .41	25	11341	97.94	1066.42	.109	<.0001
Woman	.07	.01 - .14	9	5643	82.60	38.33	.008	.03
Education	.05	-.12 - .22	13	6471	97.83	424.83	.099	.55
Income	.04	.004 - .07	9	3659	5.81	7.98	.0002	.03
Perceived cost	-.31	-.45 - -.14	22	9903	98.59	1746.64	.162	.0003

Note: *k represents the number of studies that have been included in the meta-analysis, n refers to the total number of participants across all the studies that have been included in the meta-analysis,* I^2 *denotes the proportion of heterogeneity attributed to differences between studies, Q represents the total heterogeneity observed in the analysis,* τ^2 *indicates the absolute heterogeneity between studies. The total number of studies in Table (k) exceeds the studies mentioned in the introduction because most studies are included in multiple analyses.*

In Figure 5 the effect sizes are shown and ranked graphically.

Figure 5 - *Mean of estimated effects for the antecedents of acceptance*



Note: *Black diamonds are used to indicate the meta-analytical effect size (r) for each specific variable. Error bars surrounding the black diamonds represent the 95% confidence interval (CI) around the effect size. Grey circles represent the effect sizes observed in individual studies included in the meta-analysis, and the size of each circle corresponds to the sample size of the respective study.*

Considering the results about acceptance, these show that the variable “Education” (r = .05; p = .55) has no significant effect on the technologies acceptance, while the variables with a small effect are “Income” (r = .04; p < .05) and “Woman” (r = .07; p < .05). The variables “Subjective knowledge” (r = .30; p < .001), “Ecological lifestyle” (r = .32; p < .01), “Perceived technology reliability” (r = .32; p < .001), “Personal norm” (r = .32; p < .05), “Climate change concern” (r = .37; p < .001), “Perceived behavioral control” (r = .38; p <.

001), “Consumer innovativeness” ($r = .39$; $p < .01$), “Social norms” ($r = .39$; $p < .001$), “Perceived ease of use” ($r = .41$; $p < .001$), “Perceived benefits” ($r = .42$; $p < .001$), “Trust in decision makers” ($r = .43$; $p < .001$), “Government initiatives” ($r = .45$; $p < .01$) have a medium effect on acceptance. Finally, the only variable to have a large effect on acceptance turns out to be the variable “Acceptability” ($r = .52$; $p < .001$).

2.3.1 Moderation analysis

Due to the presence of substantial heterogeneity among effect sizes from individual studies, moderation analyses were conducted to interpret this heterogeneity across studies. Different moderators were hypothesized, some were considered for all variables, and others were specific for certain variables. The moderators used for all variables are type of technology (mitigation or adaptation technologies), year of publication, impact factor (IF) of the journal, sample origin (eastern/western), sample type (local/general), Global Innovation Index of the publication year of the country of origin of the sample, and the sample mean age. The Global Innovation Index (GII) is released annually since 2007 by the World Intellectual Property Organization (WIPO), the Confederation of Indian Industry (CII), and the Institut Européen d’Administration des Affaires (INSEAD). Its main objective is to assess and compare the innovation capacities and achievements of nations and regions globally, relying on a comprehensive array of data sources.

Moderators used only for specific meta-analyses are intention type (only for meta-analyses with DV acceptance; i.e., intention to buy, to use, or to support the technology); and norm type (only for the meta-analysis with dependent variable [DV] acceptance and independent variable [IV] social norms, i.e., descriptive and injunctive social norms).

Although several moderators have been hypothesized to explain such heterogeneity, it has not always been possible to test such moderations because of the small number of studies on some variables (6–10 being the recommended threshold for continuous moderators; Fu et al.,

2011) or the absence of studies for each categorical moderator (4 being the recommended threshold for each category of the categorical moderators; Fu et al., 2011).

Given the large number of meta-analyses conducted and moderators tested, considering categorical moderators, only significant results emerging from the moderation analyses are reported. No significant effects emerged when considering acceptability as DV. Considering acceptance as DV (Table 7), a significant effect of the moderator “Sample origin” emerged in influencing the relationship between “Perceived behavioral control” and “Subjective knowledge” with acceptance. “Perceived behavioral control” and “Subjective knowledge” influence acceptance more in eastern (respectively: $r = .49$; $p < .001$; $r = .33$; $p < .001$) than western (respectively: $r = .23$; $p < .01$; $r = -.003$; $p = .98$) samples. On the other hand, the relationship between “Climate change concern” and acceptance is stronger considering solar energy ($r = .51$; $p < .001$) when compared with other technologies ($r = .27$; $p < .001$). Finally, the type of intention (support, use, buy) influences the relationship between IVs “Acceptability”, “Perceived Benefits”, and “Perceived behavioral control” with DV acceptance. “Acceptability” influences the most “Intention to support” ($r = .81$; $p < .001$) than “Intention to use” ($r = .35$; $p < .05$) and “Intention to buy” ($r = .49$; $p < .001$). “Perceived behavioral control” influence the most “Intention to support” ($r = .60$; $p < .001$) than “Intention to use” ($r = .41$; $p < .01$) and “Intention to buy” ($r = .28$; $p < .001$). “Perceived benefits” influence the most “Intention to buy” ($r = .49$; $p < .001$) than “Intention to use” ($r = .37$; $p < .001$) and “Intention to support” ($r = .20$; $p = .06$).

Table 7 - *Moderation analysis for Acceptance determinants*

Independent variables	***r***	***p***	R^2
Attitude			
Moderator: Intention type		<.01	25.05%
Intention to use	.35	<.05	
Intention to buy	.49	<.001	
Intention to support	.81	<.001	
Perceived benefits			
Moderator: Intention type		<.05	15.72%
Intention to use	.37	<.001	
Intention to buy	.49	<.001	
Intention to support	.20	.06	
Perceived behavioral control			
Moderator: Intention		<.05	23.28%
Intention to use	.41	<.01	
Intention to buy	.28	<.001	
Intention to support	.60	<.001	
Perceived behavioral control			
Moderator: Sample origin		<.01	23.12%
East	.49	<.001	
West	.23	<.01	
Subjective knowledge			
Moderator: Sample origin		<.05	19.19%
East	.33	<.001	
West	-.003	.98	
Climate change concern			
Moderator: Solar/other		<.001	36.13%
Solar	.51	<.001	
Other	.27	<.001	

As for continuous moderators, all moderations are reported. These results are reported in Tables 8 and 9. Considering acceptability as DV, year of publication positively moderates the relationship between "Income" and acceptability ($r = .01$; $p < .05$); journal impact factor negatively moderates the relationship between "Positive emotional response" and acceptability ($r = -.09$; $p < .001$); and average age of the sample positively moderates the relationship between “Positive emotional response” (r = .03; p < .01) and “Conservative” (political orientation, r = .06; p < .05) with acceptability.

Table 8 - *Moderation analysis for Acceptability determinants (all continuous moderator)*

Independent variables	**Continous moderators**					
	Publication Year		**Impact Factor**		**Age**	
	r	***p***	***r***	***p***	***r***	***p***
Perceived benefits	-.003	.87	.04	.32	-.01	.42
Positive emotional response	-.01	.77	**-.09**	**<.0001**	**.03**	**<.01**
Fairness	.03	.46	.06	.39	-.004	.87
Trust in decision makers	-.005	.78	.02	.46	-.004	.52
Perception of human impact on climate change	-.003	.86	-.01	.65	.005	.68
Climate change concern	.01	.51	.01	.73	.002	.74
Place attachment	-.01	.54	.02	.56	.001	.97
Subjective knowledge	.005	.79	-.003	.92	.001	.92
Income	**.01**	**<.05**	-.01	.19	.0002	.92
Education	-.01	.12	-.001	.86	.002	.48
Woman	.01	.08	.01	.19	.01	.16
Conservative	-.001	.87	.01	.15	**.06**	**<.05**
Negative emotional response	NA	NA	NA	NA	NA	NA

Considering acceptance as DV, publication year positively moderates the relationship between “Personal norm” (r = .19; p < .001), “Perceived technology reliability” (r = .03; p < .001), and “Education” (r = .06; p < .05) with acceptance, while negatively moderating the relationship between “Woman” (gender, r = −.03; p < .01) and “Perceived cost” (r = −.08; p < .01) with acceptance. Journal impact factor negatively moderates the relationship between “Trust in decision makers” (r = −.10; p < .05) and “Consumer innovativeness” (r = −.05; p < .05) with acceptance, while positively moderating the relationship between “Woman” (gender, r = .01; p < .05) and acceptance. The GII of publication year negatively moderates the relationship between IVs “Government initiatives” (r = −.03; p < .01), “Perceived benefits” (r = −.01; p < .01), “Perceived technology reliability” (r = −.01; p < .01), “Subjective knowledge” (r = −.01; p < .01), and “Woman” (gender, r = −.01; p < .01) with acceptance. Finally, the average age of the sample positively moderates the relationship between "Education" (r = .02; p < .05) and acceptance, while it negatively moderates the relationship between "Perceived behavioral control" (r = −.01; p < .05), "Subjective knowledge" (r = −.01; p < .05), and "Woman" (gender, r = −.01; p < .05) with acceptance.

Table 9 - *Moderation analysis for Acceptance determinants (all continuous moderator)*

Independent variables	**Continous moderators**							
	Publication Year		**Impact Factor**		**GII of Publication Year**		**Age**	
	r	***p***	***r***	***p***	***r***	***p***	***r***	***p***
Attitude	-.004	.88	-.01	.68	-.002	.66	-.006	.47
Government initiatives	.08	.35	-.20	.12	**-.03**	**<.01**	NA	NA
Trust in decision makers	.04	.40	**-.10**	**<.05**	-.01	.53	-.02	.18
Perceived benefits	.01	.33	.02	.15	**-.01**	**<.01**	-.01	.28
Perceived ease of use	.01	.81	-.04	.10	.004	.64	NA	NA
Social norms	.03	.24	-.03	.23	.001	.84	-.01	.45
Consumer innovativeness	-.004	.94	**-.05**	**<.05**	NA	NA	NA	NA
Perceived behavioral control	.02	.39	-.01	.58	-.01	.20	**-.01**	**<.05**
Climate change concern	.02	.30	-.01	.62	-.005	.23	-.01	.17
Personal norm	**.19**	**<.001**	-.06	.20	-.003	.81	.03	.08
Perceived technology reliability	**.03**	**<.001**	.01	.69	**-.01**	**<.01**	NA	NA
Ecological lifestyle	-.03	.56	-.11	.09	-.02	.08	-.04	.43
Subjective knowledge	.02	.48	.02	.32	**-.01**	**<.01**	**-.01**	**<.05**
Woman	**-.03**	**<.01**	**.01**	**<.05**	**-.01**	**<.01**	**-.01**	**<.05**
Education	**.06**	**<.05**	-.01	.51	NA	NA	**.02**	**<.05**
Income	-.002	.65	NA	NA	NA	NA	-.001	.74
Perceived cost	**-.08**	**<.01**	.01	.61	.01	.20	NA	NA

2.4 Discussion

Considering the results emerging from the two series of meta-analyses on the predictors of acceptability and acceptance of renewable and sustainable, mitigation and adaptation, energy technologies, variables referring to the adopting person, the technology to be adopted, or the context of adoption emerge as the main predictors.

Among both the determinants of acceptability and acceptance, findings identified three clusters of variables related to the adopting person's beliefs, classified according to the magnitude of the effect of their relationship with the DV and according to their theoretical content.

Considering acceptability determinants, the identified clusters of variables are the following ones:

- Sociodemographic variables ("Woman", "Education", "Income") and political orientation ("Conservative") report a small-to- no effect;
- Variables regarding a mostly cognitive relation of the individual adopter with the adopted technology and its surroundings ("Subjective knowledge", "Climate change concern", "Perception of human impact on climate change"), as well as the affective relation with the context (i.e., "Place attachment"), and "Trust in decision makers" report small-to-medium effects;
- Variables regarding an affective relation of the individual adopter with the adopted energy technology ("Positive emotional response" and "Negative emotional response"), as well as the relevant adoption social process ("Fairness"), report medium and medium-to-large effects.

It is important to emphasize how the emotional sphere of individuals, as well as their perceptions of themselves in relation to the context, have a greater impact than the cognitive sphere on the acceptability of sustainable energy technologies. To promote a positive attitude toward such technologies, it could therefore be possible to leverage the emotional relation of the individual with such technologies. Similarly, working on the perception of communication sources and the production and diffusion process of the technologies is crucial, as highlighted by the centrality of variables like "trust in decision makers" and perceived "fairness" respectively. The results, indeed, underscore the strong impact of perceiving the production and distribution process as fair, and the less strong, but still substantial effect of perceiving decision makers (scientists, politicians, energy entrepreneurs) as trustworthy, namely with trust based on moral integrity and/or on competence (Liu et al., 2020b).

Finally, “perceived benefits” related to the technology to be adopted appear to be the main predictor of acceptability. This emphasizes how people’s attitudes toward energy technologies are strongly influenced by the characteristics of the technology in terms of their perceived (from the point of view of the public) environmental, economic, and societal impacts (e.g., CO_2 emissions reduction, tax benefits, and economic growth).

Considering the acceptance determinants of these technologies, the clusters identified slightly deviate from those concerning acceptability predictors, although the general pattern is very similar:

- Sociodemographic variables (“Income”, “Education”, “Woman”) report a small-to-no effect;
- Variables related to the cognitive sphere of the adopter (“Subjective knowledge”, “Ecological lifestyle”, “Personal norm”, “Climate change concern”, “Perceived behavioral control”, and “Consumer innovativeness”) report medium effects;
- Variables related to the adopters’ perceptions about the context (“Social norms”, “Trust in decision makers”) and their “Acceptability” toward the specific technology report medium-to-large effects.

Confirming classical theories (Ajzen, 1991) and the specific framework of this contribution (Bonaiuto et al., 2024), attitude (acceptability) emerges as the main predictor of intention (acceptance). Among the adopter-related variables, those that seem to have the greatest impact on acceptance, in addition to acceptability, appear to be variables that relate the individuals to their social context (i.e., “Social norms”, “Trust in decision makers”).

It is noteworthy that this also emerged among the predictors of acceptability, highlighting how social context (as well as social pressure) can drive our attitudes and intentions regarding the energy context as well. This could motivate and sway the global population's behavior, encouraging them to adopt pro-environmental actions, including their embrace of renewable and sustainable energy technologies.

Moreover, an important result is the sociodemographic variables' limited ability to influence the acceptability and acceptance of renewable and sustainable energy technologies. On the contrary, self-beliefs about self-reported psychological variables, as well as the beliefs about the technology and the context of adoption, have a medium-to-large impact. Future research could therefore focus more on this type of variable rather than focusing on the specific effects of socio-demographic variables.

In fact, meta-analyses that investigated predictors of acceptance revealed the importance of variables related to the context of adoption ("Government initiatives") and the technology to be adopted ("Perceived technology reliability", "Perceived ease of use", "Perceived benefits") in influencing people's decisions, reporting medium-to-large effects. Despite the centrality of social-psychological variables, it is then crucial that a specific energy technology is perceived as useful, effective, and reliable and that its implementation is accompanied by government incentives (e.g., tax deductions for energy efficiency, etc.).

The results that emerged from the moderation analyses (see Tables 7 to 9) showed that some of the moderators captured part of the heterogeneity of the meta-analyses (although future contributions need to deepen this issue by recurring to larger data sets).

Considering bibliometric moderators, the "publication year" influences the results. More recent articles show stronger relationships between some IVs ("Income", "Personal norm", "Perceived technology reliability", and "Education") and the acceptability and acceptance of the energy technologies examined. This may be due to the increase in the use of these technologies in recent years. This, particularly regarding “Perceived technology reliability” and “Education”, could be related to an increased perception of the reliability of such technologies and awareness during educational pathways, respectively. More recent research, on the other hand, presents a weaker relationship between “Woman” (gender) and “Perceived cost” toward acceptance. This could be due, as far as “Perceived cost” is concerned, to the fact that as the number of technologies and their use increases, perceiving them as expensive may bother potential users more than in the past, when certain technologies seemed very distant and reserved to a small segment of society. The publishing journal’s IF also explains part of the heterogeneity that emerged. Moderations show that research published in journals with higher impact factors report weaker associations between predictors (“Positive emotional response”, “Trust in decision makers”, “Consumer innovativeness”, and “Woman”) and technology acceptability and acceptance: It is probably due to greater methodological standards required in for publishing in top ranking journals. The innovativeness of the sample’s country of origin (GII) also has a negative impact on the relationship between IVs (“Government initiative”, “Perceived benefits”, “Perceived technology reliability”, “Subjective knowledge”, and “Woman”) and DVs. This could potentially be due to a kind of “ceiling effect” on social acceptance. In fact, in more innovative countries, the threshold of social acceptance might be high enough not to be significantly impacted by the predictor variables.

Regarding sociodemographic moderators, the sample “average age” positively affects the relationship between “Positive emotional response” and “Conservative” (political orientation) on acceptability and “Education” on acceptance, while it negatively affects the relationship between “Perceived behavioral control”, “Subjective knowledge”, and “Woman” on acceptance. This could be explained, with reference to negative moderations, by older people's both lower perceived control and knowledge of technology. These factors can, therefore, be a barrier to the social acceptance of such technologies by the elderly population.

The tripartite intention (acceptance) type can also explain the emerged heterogeneity. Acceptability toward a particular technology has more influence on the intention to support it socially and politically, while the "Perceived benefits" of the technology have more influence on the intention to purchase it (Bonaiuto et al., 2024). This could be explained by the fact that perceived benefits, since they are often linked to the economic benefits for the adopter, may have more influence on the intention to proactively move toward the individual purchase of a given technology. On the other hand, acceptability, being a favorable orientation toward a technology, would be able to mobilize social proactivity.

The relationship between "Perceived behavioral control" and "Subjective knowledge" toward energy technology and social acceptance is positively moderated by the samples' country origins. Particularly, this relationship is stronger in Eastern countries, than in Western countries. Such moderation effects require closer consideration of the role that cultural contexts and norms play in the social acceptance process.

Finally, "Climate change concern" influences the acceptance of solar energy more than that of other technologies. This could be due to the perception of solar energy as more reliable (because it is more widely used) and less risky than other technologies, leading people who are more concerned about climate change to rely on "safer" and greener technology.

Hence, regarding social-psychological constructs, the results highlight the centrality of two variables widely studied in environmental psychology as PEBs promoters and, specifically, as SETs acceptance promoters: social norms and trust in decision-makers. Given the ease of intervention associated with implementing persuasive measures through normative messaging (see paragraph 1.4) and the robust empirical support for the efficacy of social norms in promoting PEBs (Farrow et al., 2017) − including meta-analytic evidence (Abrahamse &

Steg, 2013; Bergquist et al., 2019) − future research should focus on how these norms interact with other variables (e.g., mediators or moderators) to influence the social acceptance of SETs. Although the current study did not find significant moderations regarding the specific effects of injunctive and descriptive norms, nor differences in the impact of social norms between mitigation and adaptation technologies, these remain highly relevant areas of inquiry that require further investigation. This is especially pertinent given the limited number of studies exploring the effect of social norms on the social acceptance of adaptation technologies.

Additionally, the findings underscore the importance of emotional responses in shaping the acceptability of these technologies. However, given the paucity of studies examining the impact of emotional reactions on the social acceptability and acceptance of SETs (see Tables 5 and 6), future research should also investigate how perceptions of risks and benefits associated with these technologies influence individuals' emotional responses, as these emotions, in turn, impact future acceptability and acceptance. In fact, only a few studies (e.g., Cousse, 2021; Cousse et al., 2020; Cousse et al., 2021) have emphasized the critical role of emotional components in facilitating or hindering the social acceptance of SETs.

Building on the theoretical framework outlined in paragraphs 1.3 and 1.4, as well as the results of the present study, it is essential for future research to examine these two variables − not only independently but also in interaction with one another. This includes exploring how emotional responses to the technology and its adoption context (i.e., social norms) can significantly influence individual decision-making.

Finally, while the findings suggest that factors closely tied to individual characteristics have a minor impact on the social acceptance of SETs, it is crucial to recognize the role of variables extensively studied in environmental psychology, such as personal norm. Personal norm has been identified as a critical driver of PEBs (Harland et al., 1999) and, more specifically, the acceptance of SETs (Steg & De Groot, 2010). Moreover, previous research highlighted how personal norm strongly interacts with crucial variables, such as social norms (see De Groot et al., 2021). This is also corroborated by the perspective of the theoretical model proposed by Bonaiuto and colleagues (2023, 2024), which suggests that investigating various types of beliefs remains fundamental to fully understanding the processes that lead individuals to support, purchase, and adopt SETs.

CHAPTER 3

Study 2

3.1 Aim of the study

Study 2 addresses two main overarching objectives:

a) Building on the meta-analyses' findings (Milani, Dessi, & Bonaiuto, 2024; Study 1) and drawing upon the theoretical model proposed by Bonaiuto et al. (2024), Study 2 focuses on the adopter's beliefs. Specifically, this study seeks to identify three key predictors - adopters' beliefs about themselves, their relationship with the technology being adopted, and their relationship with the adoption context - that influence the acceptability and acceptance of SETs. With a specific emphasis on the central role of normative influence (as outlined in the Norm Activation Theory; Schwartz, 1968, 1977, and the Focus Theory of Normative Conduct; Cialdini et al., 1990, 1991) - which has been extensively studied to understand PEBs drivers (see Chapter 1) - this study considers personal norm (namely, the expectations that stem from integrated values and a duty to participate in specific behaviors reflecting the commitment to the same values) as the adopter belief about himself/herself and social norms (namely, the perception of the implicit social rules that govern behavior within a community) as the adopter beliefs about the adopter's relationship with the adoption context. Furthermore, given the central role of emotions in promoting the social acceptability and acceptance of SETs (as revealed in Study 1; Milani, Dessi, & Bonaiuto, 2024), Study 2 examines emotional responses to risks and benefits associated with the technology (namely, the expected affective impact the behavior – in this case, adopting a specific technology – causes on the individuals) as the adopter beliefs concerning the adopter's relationship with the technology.

In summary, the first main objective is to empirically test an adaptation of the theoretical model proposed by Bonaiuto et al. (2024).

b) The second main objective of Study 2 is to examine how different acceptability characteristics may influence the acceptance of these technologies through graphical models (i.e., psychometric network analysis; PNA).

   While the use of such models is still in its early stages and the network approach has not yet been applied to the study of acceptability for SETs, on the other hand environmental psychologists have begun employing graphical models (e.g., Gaussian Graphical Models, Bhushan et al., 2019) to test their hypotheses (see Zwicker et al., 2020).

c) Finally, the study aims to investigate and highlight potential differences and/or similarities between mitigation and adaptation energy technologies in their social acceptance process. Particularly, as no significant differences between mitigation and adaptation technologies emerged from the results of Study 1 (Milani, Dessi, & Bonaiuto, 2024), no substantial differences in the social acceptance process of these technologies are hypothesized.

Building on the outlined objectives, Study 2 aims to provide novel theoretical and applied insights into the field of SETs' social acceptance through a multi-method approach. Situated within the theoretical framework proposed by Bonaiuto and colleagues (2023, 2024), this study seeks to deliver an initial empirical validation of the model by testing the effects of specific beliefs within each cluster (i.e., personal norm, social norms, and emotional responses). The selection of these beliefs stems not only from the findings of Study 1 (Milani, Dessi, & Bonaiuto, 2024) but also from their prominence in the literature on decision-making processes related to PEBs, as informed by TNC (Cialdini et al., 1990, 1991) and NAT (Schwartz, 1968, 1977). These theories respectively suggest that PEBs are guided by social and personal norms, emphasizing that PEBs are closely tied to individual identity, carry solid moral significance (Van der Werff et al., 2013), and are often driven by self-representation. This socially constructed self-representation (see Abrams & Hogg, 2010) prompts individuals to reflect on their own and others' morality and behaviors before acting. Numerous studies have indeed explored how these norms can operate independently (e.g., Barth et al., 2016; Toft et al., 2014; van der Werff & Steg, 2016), in parallel (e.g., Fornara et al., 2016; Han, 2014; Rezaei & Ghofranfarid, 2018), or interactively (e.g., De Groot et al., 2021) to promote PEBs in general and SETs' social acceptance specifically.

Findings from Study 1 (Milani, Dessi, & Bonaiuto, 2024) further highlighted the central role of emotions in driving the acceptability of SETs. These results reinforce what is well-established in psychology: individual actions, particularly those with substantial moral implications like PEBs, are significantly influenced by emotional factors (see Baumeister et al., 2007). Furthermore, when individuals encounter new or uncertain stimuli, emotional responses (e.g., fear) associated with those stimuli can strongly influence behavioral outcomes (for an example related to nuclear energy acceptance, see Keller et al., 2012). Specifically, negative emotional experiences drive individuals to avoid the same stimuli in the future, while positive emotions encourage approaching them (Behavioral Inhibition/Approach Systems; Gray, 1990).

Regarding the second main objective, this study investigates how the perceptions of SETs and, specifically, their particular aspects can facilitate support and adoption. To address this objective, graphical methods were chosen, as several studies have demonstrated that Causal Attitude Network (CAN) models are among the most effective tools for studying attitudes and their impact on intentions and behaviors (Dalege et al., 2016, 2017, 2019; Zwicker et al., 2020). Dalege and colleagues (2016), highlighting the need to develop a formalized measurement model of attitudes, demonstrated the unrealistic nature of considering attitude items or indicators as independent. Instead, they emphasized the importance of measuring interdependencies between various attitude components and the attitude itself. By addressing this issue, the authors underline that network approaches are the most effective method for exploring causal relationships between attitudes and behaviors (or intentions).

3.1.1 Hypotheses

The specific hypotheses related to each overarching objective are outlined below.

For the first overarching objective (a), the following hypotheses are formulated:

> H1a: “Positive Affective Response” directly and positively correlates with “Acceptability” (mediator) and Acceptance (i.e., “Support Intention” and “Intention to Use & Pay”; DVs).
>
> H2a: “Social Norms” directly and positively correlate with “Acceptability” (mediator) and Acceptance (i.e., “Support Intention” and “Intention to Use & Pay”; DVs).
>
> H3a: “Personal Norm” directly and positively correlates with “Acceptability” (mediator) and Acceptance (i.e., “Support Intention” and “Intention to Use & Pay”; DVs).
>
> H4a: “Acceptability” directly and positively correlates with Acceptance (i.e., “Support Intention” and “Intention to Use & Pay”; DVs). Additionally, “Acceptability” mediates the indirect relationship between the adopters’ beliefs (i.e., “Positive Affective Response”, “Social Norms”, and “Personal Norm”; IVs) and Acceptance (i.e., “Support Intention” and “Intention to Use & Pay”; DVs).
>
> H5a: The model is structurally invariant across mitigation and adaptation technologies.

The second overarching objective (b) is purely exploratory. The only hypothesis formulated is as follows:

> H1b: The attitude (acceptability) network structure is invariant between mitigation and adaptation energy technologies.

3.2 Method

3.2.1 Participants

The total sample consisted of 726 Italian participants recruited via Prolific.

Participants were randomly exposed (balanced by gender) to one of two information scenarios about mitigation or adaptation energy technologies. They then answered the questionnaire (developed in Qualtrics) about the technologies whose information scenario they had read.

The "mitigation" sample comprised 366 participants (mean age = 34.50, *sd* = 11.80, min = 18, max = 73). Concerning gender, the sample consisted of 195 women (53.3 %), 165 men (45.1 %), 3 third gender/non-binary (0.8 %), and 3 preferred not to answer (0.8 %).

The "adaptation" sample comprised 360 participants (mean age = 34.10, *sd* = 10.90, min = 18, max = 72). Concerning gender, the sample consisted of 189 women (52.5 %), 164 men (45.6 %), 4 third gender/non-binary (1.1 %), and 3 preferred not to answer (0.8 %).

Participants who did not finish the questionnaire, who completed the questionnaire in inadequate time (either too quickly or too slowly), who failed at least two attention checks, and who did not answer all items of the presented measurement scales were excluded during data collection.

3.2.2 Tool and procedures

The study followed the Ethical Principles of Psychologists and Code of Conduct of the American Psychological Association (APA). It was approved by the Ethics Committee of Sapienza University of Rome (Approved in June 2024; protocol number: CERT_18FAC21E00A).

Following informed consent for data processing, participants were randomly assigned to read an information scenario (either related to mitigation or adaptation energy technologies), which introduced the technologies by explaining what they are, how they work, their objectives, and providing relevant examples. These informational scenarios were included because the technologies presented - particularly adaptation technologies - are relatively unknown to the general public, and them could provide a concise overview of these technologies. The scenarios were designed to offer a “neutral” representation of the technologies, focusing solely on the technologies’ objectives and functions, providing technologies examples. Before being used in the present study, the mitigation and adaptation scenarios were tested in a pilot study, which demonstrated their non-differentiability across specific dimensions such as optimism ($t_{(38)}$ = 1.72; p = .09), realism ($t_{(38)}$ = .69; p = .50), social justice ($t_{(38)}$ = 1.48; p = .15), and political ideology ($t_{(38)}$ = .44; p = .66). The information scenarios presented to participants in Study 2 are detailed in Appendix B. Following the information scenario, participants were asked to complete a self-report questionnaire containing questions related to the technologies presented and encompassing the following measures (also detailed in Appendix B):

- *Social Norms* (adapted from Fornara et al., 2016): consisting of 6 items (e.g., “*Most people important to me would approve if I adopted such technologies to counter* *climate change*”), with a 5-step Likert response scale (from 1 = “*Strongly disagree*” to 5 = “*Strongly agree*”) (α[2] = .87/.88).

- *Personal Norm* (adapted from Abrahamse & Steg, 2009): consisting of 3 items (e.g., “*I feel guilty if I do not use/purchase/support such technologies*”), with a 5-step Likert response scale (from 1 = “*Strongly disagree*” to 5 = “*Strongly agree*”) (α = .74/.79).
- *Positive Affective Response* (adapted from Mackinnon et al., 1999): consisting of 7 items (e.g., “*Thinking about the technologies previously presented, and their possible benefits and risks, makes me feel excited*”), with a 7-step Likert response scale (from 1 = “*Doesn’t describe me at all*” to 7 = “*Completely describes me*”) (α = .86/.83).
- *Acceptability* (adapted from Yazdanpanah et al., 2015): consisting of 3 items (e.g., “*I think such energy technologies are valuable*”), with a 10-step Likert response scale (from 1 = “*Strongly disagree*” to 10 = “*Strongly agree*”) (α = .84/.91).
- *Technology Acceptability* (Bonaiuto et al., 2024): a semantic differential was used to measure the acceptability towards the technologies consisting of 12 adjective pairs (e.g., “*I believe such energy technologies are unsafe/safe*”), with a 10-step Likert response scale (α = .93/.95).
- *Support Intention* (adapted from Huijts et al., 2014): consisting of 7 items (e.g., “*If there were a discussion regarding the use of such energy technologies, how likely would you be to take the following actions in favor of them? Sign a petition*”), with a 7-step Likert response scale (from 1 = “*Definitely wouldn’t*” to 7 = “*Definitely would*”) (α = .88/.88).
- *Intention to Use & Pay* (adapted from Francis., 2004): consisting of 6 items (e.g., “*I plan to spend money to ensure such technologies are adopted to counter climate*

[2] The two values reported for Cronbach’s alpha reflect the measure’s reliability within the “mitigation” and “adaptation” samples, respectively, before and after the separation bar.

change"), with a 5-step Likert response scale (from 1 = "*Strongly disagree*" to 5 = "*Strongly agree*") (α = .88/.91).

In this study, two different measures were initially employed to assess acceptability toward the technologies (i.e., "Acceptability" and "Technology Acceptability"). Given the centrality of the acceptability construct, this approach was adopted to effectively manage potential issues related to verifying assumptions. Upon further analysis, the "Acceptability" measure was selected to test the first overarching objective. This decision was made because the "Technology Acceptability" measure exhibited significant multicollinearity with the "Intention to Use & Pay" measure in the "adaptation" sample (r = .74), which would have compromised the reliability and interpretability of the regression coefficients. Given the high correlation between the two acceptability measures in both the "mitigation" and "adaptation" samples (r = .86 and r = .93, respectively), selecting the more parsimonious "Acceptability" measure allowed to avoid multicollinearity issues, ensuring that the model's estimates were more stable and the results more reliable. However, the individual items of the "Technology Acceptability" measure were still used to test the second overarching objective, as they were more suitable for that purpose and not subject to multicollinearity.

3.2.3 Data Analysis

Two different approaches were employed to test the hypotheses mentioned above: i.e., path analysis for the first overarching objective, and PNA for the second one – by using the same sample of participants.

Regression analyses were conducted to test the hypotheses related to the first overarching objective (H1a to H5a). Specifically, a multi-group path model was developed to verify whether the model was stable and structurally invariant across the two energy technology groups (mitigation and adaptation). These research hypotheses were tested using R (version 4.3.2) with the "lavaan" package (version 0.6-17). The sample size required to test these hypotheses was determined via an “A priori Power Analysis” conducted in R (version 4.3.2) using the “mbess” package (version 4.9.3). Through the “ss.power.sem” function, the number of participants required to achieve a power of .80 was calculated, setting a critical alpha of .05, 11 degrees of freedom (calculated based on the number of estimated parameters and the number of observed variables), and an RMSEA of .05. Since no prior research was available to base the expected RMSEA on, we opted for a conservative strategy with an acceptable RMSEA (see Schermelleh-Engel et al., 2003). This analysis indicated a requirement for 725 participants. The “A priori Power Analysis” was then replicated using the “ss.aipe.rmsea” function, with the same parameters mentioned above, except that instead of a critical alpha of .05, a confidence interval of .95 with a width of .05 was requested. This analysis indicated a requirement for 724 participants. Thus, 725 participants were deemed necessary for the path analysis.

To test the second overarching objective (specifically H1b), graphical methods (PNA) were used. This research objective was tested using R (version 4.3.2) with the “qgraph” package (version 1.9.8) (Epskamp et al., 2012) through the “graphic lasso” methodology. As for the sample size needed for PNA, there are no established formulas for adequately calculating statistical power. However, it is well-documented in the literature (Dalege et al., 2016; Epskamp & Fried, 2018) that for networks of moderate size (up to 25 nodes) based on continuous data, a sample size of 250 participants is sufficient. Given that our attitude (acceptability) networks - focused on “Support Intention” and “Intention to Use & Pay”, for both mitigation and adaptation technologies - comprise 13 nodes each (12 “Technology Acceptability” items + a general intention measure), 250 participants for each energy technology group (500 participants) would have been sufficient for these analyses.

However, given the need to recruit 725 participants as determined by the power analysis for the path analysis (first overarching objective), data collection was conducted on this sample size, which was sufficient for both types of analyses.

3.3 Results

3.3.1 Descriptive statistics and correlations

To assess the univariate normality of the distribution of the variables used in the path model and to investigate multicollinearity among variables, descriptive statistics were conducted, and linear correlations (Pearson's *r*) between the variables were examined (see Table 10).

The "Technology Acceptability" measure was not examined as the assumptions will not need to be tested, given that in the PNA, individual items of the measure, rather than its average, will be treated as nodes.

Table 10 - *Descriptive statistics and bivariate correlations*

	1	2	3	4	5	6
1. Positive Affective Response	-	.43**	.33**	.43**	.41**	.48**
2. Personal Norm	.52**	-	.42**	.49**	.51**	.54**
3. Social Norms	.42**	.55**	-	.45**	.65**	.54**
4. Acceptability	.52**	.63**	.57**	-	.61**	.51**
5. Intention to Use & Pay	.50**	.67**	.67**	.69**	-	.61**
6. Support Intention	.53**	.58**	.55**	.61**	.64**	-
Mean	4.11/3.87	3.57/2.99	3.62/3.28	4.52/3.95	3.85/3.32	4.29/3.68
Standard deviation	1.19/1.18	.89/.95	.81/.85	.67/.94	.83/1.00	1.45/1.49
Skewness	-.60/-.15	-.60/-.39	-.60/-.44	-1.95/-.79	-1.18/-.74	-.38/-.10
Kurtosis	.21/-.35	.11/-.40	.10/.15	5.05/.22	1.54/-.04	-.46/-.80

Note: ** p < .05, ** p < .01, *** p < .001; Correlations below the diagonal refer to the adaptation technologies (N=360), while those above the diagonal refer to the mitigation technologies (N=366); Descriptive statistics presented before the separation bar refer to mitigation technologies, while those presented after the bar refer to adaptation technologies.*

These analyses indicated no severe multicollinearity ($r < .70$) among the examined measures. Furthermore, the variables generally followed a normal distribution, reporting acceptable values of skewness and kurtosis (< 2; Garson, 2012; Field, 2009; Lomax & Hahs-Vaughn, 2012), except for the "Acceptability" measure in the "mitigation" sample, which exhibited extremely high kurtosis (k = 5.05), indicating reduced variability and severely violating the assumption of univariate normality. The Box-Cox transformation (Box & Cox, 1964) - particularly effective when non-normality is primarily due to kurtosis anomalies - was applied to address this issue, and the transformed variable (labeled as "B-C Acceptability") was included in the model.

Given the necessity to test for structural invariance between the "mitigation" and "adaptation" samples, the Box-Cox transformation was also applied to the "Acceptability" measure in the "adaptation" sample, even though this variable did not display a non-normal distribution.

Descriptive statistics for the "B-C Acceptability" measures and their correlations with other variables in both samples (mitigation and adaptation) are presented in Table 11.

Table 11 - *B-C Acceptability descriptive statistics and bivariate correlations*

	B-C Acceptability Mitigation	B-C Acceptability Adaptation
Positive Affective Response	.44**	.51**
Personal Norm	.49**	.60**
Social Norms	.45**	.53**
Intention to Use & Pay	.58**	.65**
Support Intention	.51**	.59**
Mean	4.46	3.95
Standard deviation	.64	.79
Skewness	-1.01	-.15
Kurtosis	.58	-.84

Note: ** $p < .05$, ** $p < .01$, *** $p < .001$*

3.3.2 Path analysis

To test the first overarching objective (H1a to H5a), a multi-group path analysis using Maximum Likelihood estimation with robust standard errors (to account for deviations from multivariate normality) was conducted, with the categorical variable “Technology Type” (mitigation or adaptation) as the grouping variable. Since the number of parameters to estimate equaled the number of observed data, the model was “just identified”, and it was not necessary to examine the fit indices.

Focusing on mitigation energy technologies and looking at the structural coefficients (see Figure 6 and Table 12), it emerges that “Positive Affective Response” (H1a) is positively correlated with “B-C Acceptability” (β = .24, p < .001, *SE* = .03, 95% *CI*: .07, .18) and “Support Intention” (β = .20, p < .001, *SE* = .06, 95% *CI*: .14, .36). However, “Positive Affective Response” did not show a significant correlation with “Intention to Use & Pay” (β = .08, p = .056, *SE* = .03, 95% *CI*: -.001, .11).

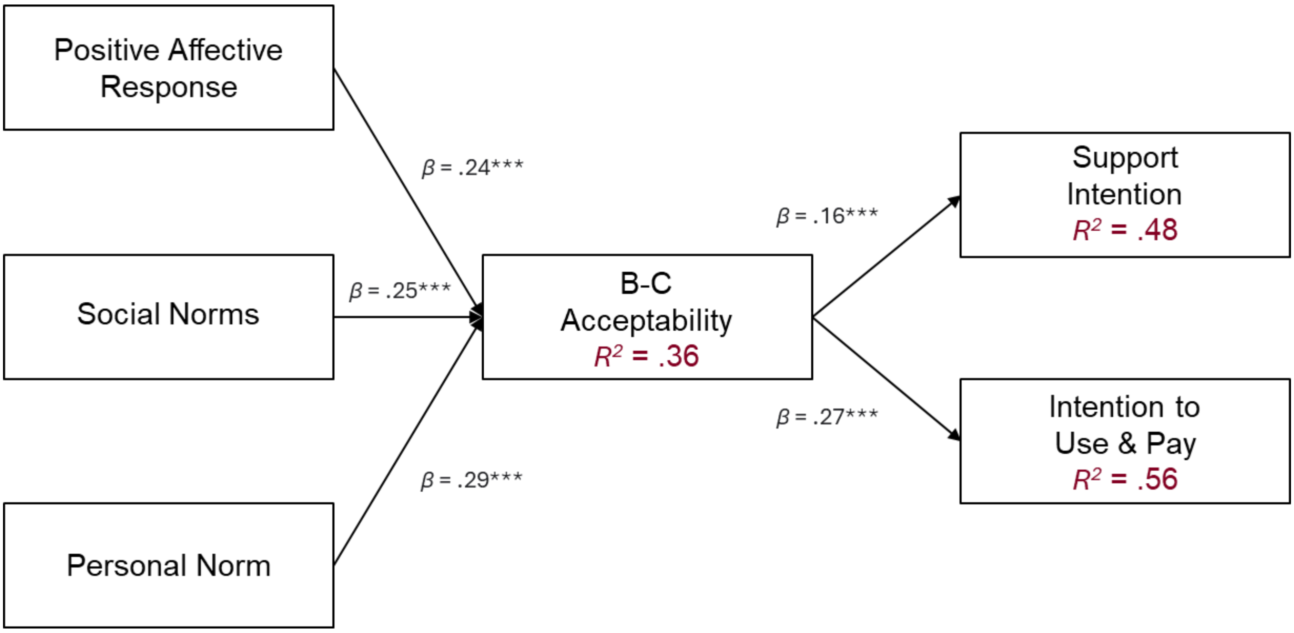
On the other hand, both “Social Norms” (H2a) and “Personal Norm” (H3a) are positively correlated with “B-C Acceptability” (respectively; β = .25, p < .001, *SE* = .04, 95% *CI*: .11, .27; β = .29, p < .001, *SE* = .04, 95% *CI*: .13, .29), “Support Intention” (respectively; β = .30, p < .001, *SE* = .08, 95% *CI*: .38, .70; β = .25, p < .001, *SE* = .08, 95% *CI*: .25, .55), and “Intention to Use & Pay” (respectively; β = .44, p < .001, *SE* = .05, 95% *CI*: .35, .56; β = .15, p = .001, *SE* = .05, 95% *CI*: .06, .23).

Regarding “B-C Acceptability” (H4a), it is positively correlated with “Support Intention” (β = .16, p < .001, *SE* = .10, 95% *CI*: .16, .57) and “Intention to Use & Pay” (β = .27, p < .001, *SE* = .06, 95% *CI*: .23, .48). Additionally, “B-C Acceptability” mediates the relationship between the three beliefs (i.e., “Positive Affective Response”, “Social Norms”, and “Personal Norm”) and Acceptance (i.e., “Support Intention” and “Intention to Use & Pay”). Specifically, “Positive Affective Response” is positively and indirectly correlated with both “Support

Intention” (β = .04, p = .006, SE = .02, 95% CI: .01, .08) and “Intention to Use & Pay” (β = .07, p < .001, SE = .01, 95% CI: .02, .07). Similarly, “Social Norms” are positively and indirectly correlated with both “Support Intention” (β = .04, p = .003, SE = .02, 95% CI: .02, .12) and “Intention to Use & Pay” (β = .07, p < .001, SE = .02, 95% CI: .03, .11). Lastly, “Personal Norm” is also positively and indirectly correlated with “Support Intention” (β = .05, p = .006, SE = .03, 95% CI: .02, .13) and “Intention to Use & Pay” (β = .08, p < .001, SE = .02, 95% CI: .04, .11).

For mitigation energy technologies, the model explains 36%, 48%, and 56% of the variance in the endogenous variables “B-C Acceptability”, “Support Intention”, and “Intention to Use & Pay”, respectively.

Figure 6 - *Mitigation Path model*



Note: ** p < .05, ** p < .01, *** p < .001*

Table 12 – *Mitigation direct and indirect effects*

	β	***SE***	**95% *CIs***
PAR → SI	.20	.06	[.14, .36]
PAR → IUP	.08	.03	[-.001, .11]
SN → SI	.30	.08	[.38, .70]
SN → IUP	. 44	.05	[.35, .56]
PN → SI	.25	.08	[.25, .55]
PN → IUP	.15	.05	[.06, .23]
PAR → ACC → SI	.04	.02	[.01, .08]
PAR → ACC → IUP	.07	.01	[.02, .07]
SN → ACC → SI	.04	.02	[.02, .12]
SN → ACC → IUP	.07	.02	[.03, .11]
PN → ACC → SI	.05	.03	[.02, .13]
PN → ACC → IUP	.08	.02	[.04, .11]

Note: *PAR = Positive Affective Response; SN = Social Norms; PN = Personal Norm; ACC= B-C Acceptability; SI = Support Intention; IUP = Intention to Use & Pay*

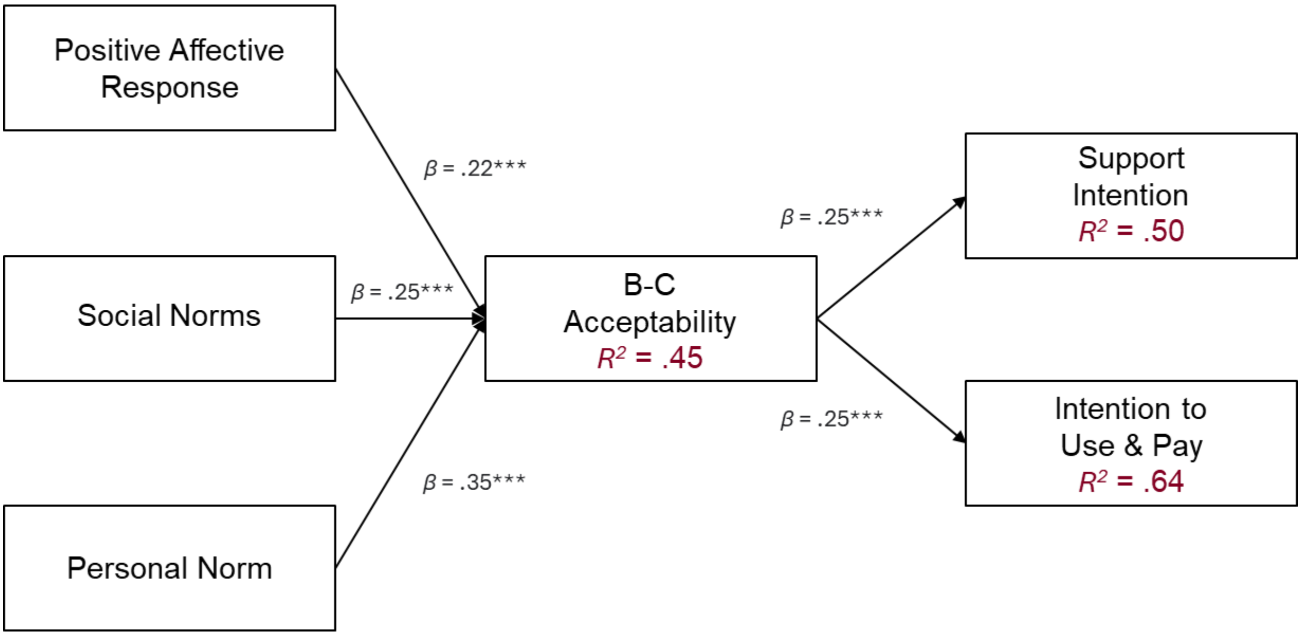
Regarding the results for adaptation energy technologies (see Figure 7 and Table 13), the analyses reveal analogous and parallel findings to those observed for mitigation technologies. Specifically, "Positive Affective Response" (H1a) is positively correlated with "B-C Acceptability" (β = .22, p < .001, *SE* = .03, 95% *CI*: .08, .21) and "Support Intention" (β = .20, p < .001, *SE* = .06, 95% *CI*: .14, .37), but does not show a significant correlation with "Intention to Use & Pay" (β = .08, p = .07, *SE* = .04, 95% *CI*: -.005, .13).

On the other hand, both "Social Norms" (H2a) and "Personal Norm" (H3a) are positively correlated with "B-C Acceptability" (respectively; β = .25, p < .001, *SE* = .05, 95% *CI*: .14, .32; β = .35, p < .001, *SE* = .05, 95% *CI*: .20, .38), "Support Intention" (respectively; β = .22, p < .001, *SE* = .09, 95% *CI*: .21, .58; β = .21, p < .001, *SE* = .09, 95% *CI*: .16, .50), and "Intention to Use & Pay" (respectively; β = .34, p < .001, *SE* = .05, 95% *CI*: .31, .50; β = .30, p < .001, *SE* = .06, 95% *CI*: .20, .44).

Regarding “B-C Acceptability” (H4a), it is positively correlated with “Support Intention” (β = .25, $p < .001$, *SE* = .11, 95% *CI*: .25, .68) and “Intention to Use & Pay” (β = .25, $p < .001$, *SE* = .06, 95% *CI*: .19, .44). Additionally, “B-C Acceptability” mediates the relationship between the three beliefs and Acceptance (i.e., “Support Intention” and “Intention to Use & Pay”). Specifically, “Positive Affective Response” is positively and indirectly correlated with both “Support Intention” (β = .05, p = .003, *SE* = .02, 95% *CI*: .02, .11) and “Intention to Use & Pay” (β = .06, p = .001, *SE* = .01, 95% *CI*: .02, .07). Similarly, “Social Norms” are positively and indirectly correlated with both “Support Intention” (β = .06, p = .001, *SE* = .03, 95% *CI*: .04, .17) and “Intention to Use & Pay” (β = .06, $p < .001$, *SE* = .02, 95% *CI*: .04, .11). Lastly, “Personal Norm” is also positively and indirectly correlated with both “Support Intention” (β = .09, $p < .001$, *SE* = .04, 95% *CI*: .06, .21) and “Intention to Use & Pay” (β = .09, $p < .001$, *SE* = .03, 95% *CI*: .04, .14).

For adaptation energy technologies, the model explains 45%, 50%, and 64% of the variance in the endogenous variables “B-C Acceptability”, “Support Intention”, and “Intention to Use & Pay”, respectively.

Figure 7 - *Adaptation Path model*



Note: ** p < .05, ** p < .01, *** p < .001*

Table 13 - *Adaptation direct and indirect effects*

	β	***SE***	**95% CIs**
PAR → SI	.20	.06	[.14, .37]
PAR → IUP	.08	.04	[-.005, .13]
SN → SI	.22	.09	[.21, .58]
SN → IUP	.34	.05	[.31, .50]
PN → SI	.21	.09	[.16, .50]
PN → IUP	.30	.06	[.20, .44]
PAR → ACC → SI	.05	.02	[.02, .11]
PAR → ACC → IUP	.06	.01	[.02, .07]
SN → ACC → SI	.06	.03	[.04, .17]
SN → ACC → IUP	.06	.02	[.04, .11]
PN → ACC → SI	.09	.04	[.06, .21]
PN → ACC → IUP	.09	.03	[.04, .14]

Note: *PAR = Positive Affective Response; SN = Social Norms; PN = Personal Norm; ACC= B-C Acceptability; SI = Support Intention; IUP = Intention to Use & Pay*

Finally, the regression paths were constrained to be equal across the two groups to test the model structural invariance between mitigation and adaptation energy technologies (H5a). The fit indices of the model with constrained regression paths were then examined, yielding satisfactory fit indices (see Schermelleh-Engel et al., 2003), as shown in Table 14. The two models - one with freely estimated regression paths and one with constrained regression paths across technologies - were compared using the scaled difference Chi-square test (Satorra & Bentler, 2001). This test indicated no significant difference between the two models (Table 15), demonstrating the structural invariance of the model across mitigation and adaptation energy technologies.

Table 14 - *Constrained model fit indices*

χ^2	*df*	*p*	χ^2*/df ratio*	*CFI*	*TLI*	*RMSEA [95% CI]*	*SRMR*
22.37	11	.02	2.03	.993	.984	.053 [.020, .085]	.044

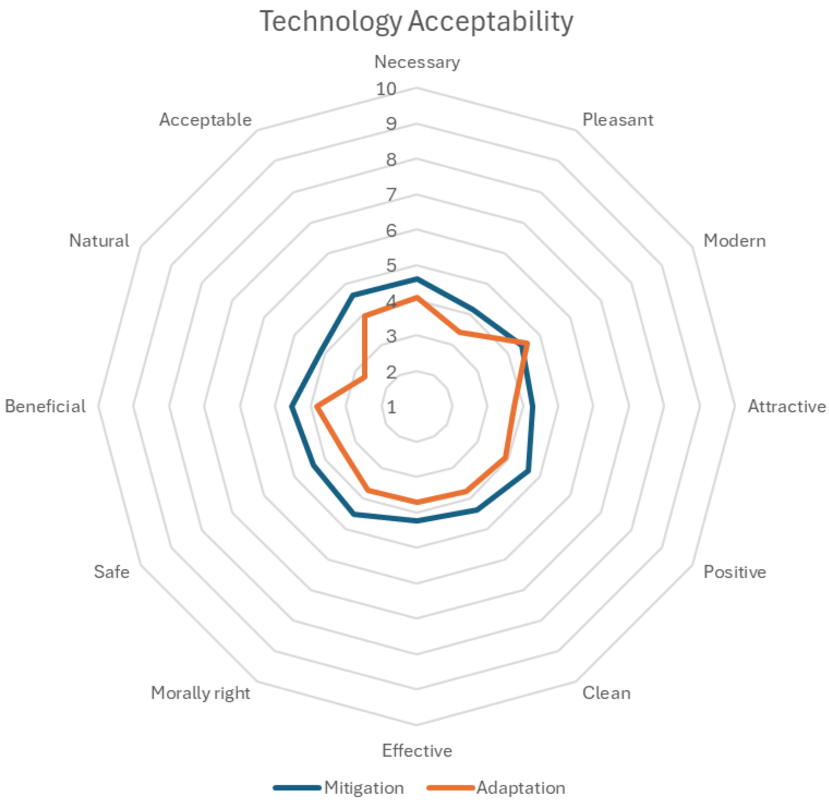
Table 15 - *Model comparison*

	df	*AIC*	*BIC*	χ^2	$\Delta\chi^2$	Δdf	$p\ (>\chi^2)$
Unconstrained Model	0	4605.8	4770.9	.00			
Constrained Model	11	4606.2	4720.8	22.37	19.36	11	.06

3.3.3 Psychometric network analysis

To address the second overarching objective (specifically H1b), network analyses were employed to examine the partial correlations between various facets of "Technology Acceptability" and Acceptance (i.e., "Support Intention" and "Intention to Use & Pay") of mitigation and adaptation SETs. The individual items of the "Technology Acceptability" measure were considered for these analyses, and their mean responses across both samples are illustrated in Figure 8. Notably, the data show that, on average, mitigation energy technologies are more accepted than adaptation technologies, which are perceived as more modern but generally less acceptable. Particularly, adaptation SETs are viewed as less natural and less pleasant than mitigation SETs. Additionally, Figure 8 highlights that the overall perception of both types of technologies and their consequent average acceptability remains relatively low.

Figure 8 - *Technology Acceptability comparison between mitigation and adaptation SETs*

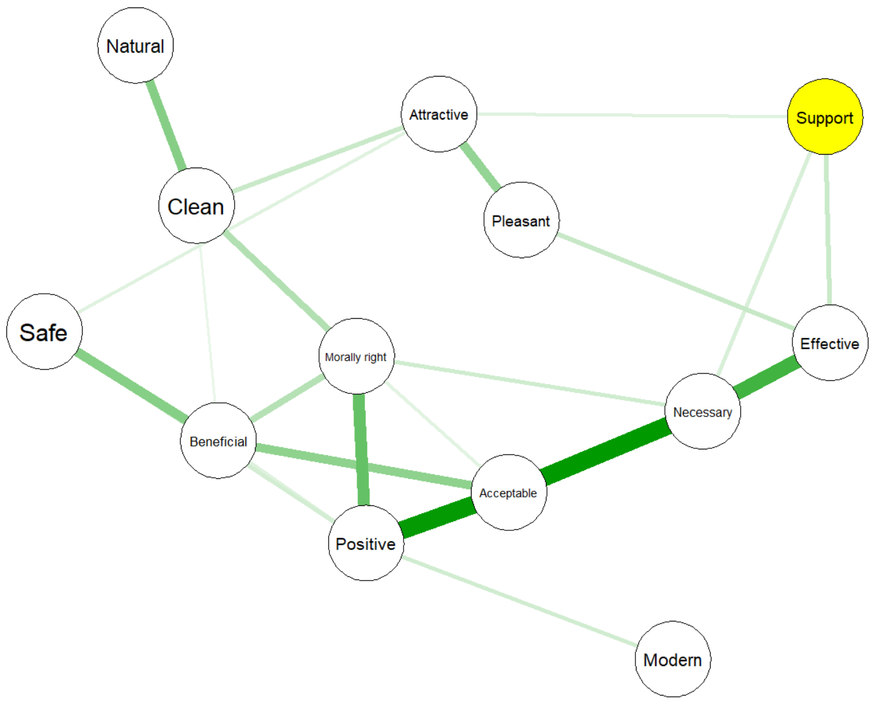


To estimate weighted, undirected networks, we followed the method described by Zwicker et al. (2020), using the *glasso* approach to create the networks. This method estimates partial correlations between each pair of variables, conditioning on all other variables, and reducing spurious partial correlations. This latter characteristic makes Gaussian graphical models a more accurate tool than linear models for conducting exploratory studies (Bhushan et al., 2019).

Specifically, four network analyses were conducted - one for each technology type (mitigation and adaptation), and separately for "Support Intention" and "Intention to Use & Pay".

For the "Support Intention" networks (Figures 9 and 10), it was found that, for mitigation technologies (Figure 9), perceiving the technologies as "Attractive", "Necessary", and "Effective" was connected to "Support Intention" (respectively: $r = 0.13$, 95% *CI*: .03, .22; $r = 0.13$, 95% *CI*: .03, .23; $r = 0.14$, 95% *CI*: .04, .24). The other nodes in the network did not show significant connections to "Support Intention".

Figure 9 - *PNA Support Intention Mitigation*



Note: *Partial correlations <.1 are not depicted; The thickness of the edges reflects the magnitude of the partial correlation between two nodes; Positive correlations are shown in green, negative in red.*

For adaptation technologies (Figure 10), only perceiving the technology as “Necessary” was found to be connected to “Support Intention” (*r* = 0.11, 95% *CI*: .01, .21).

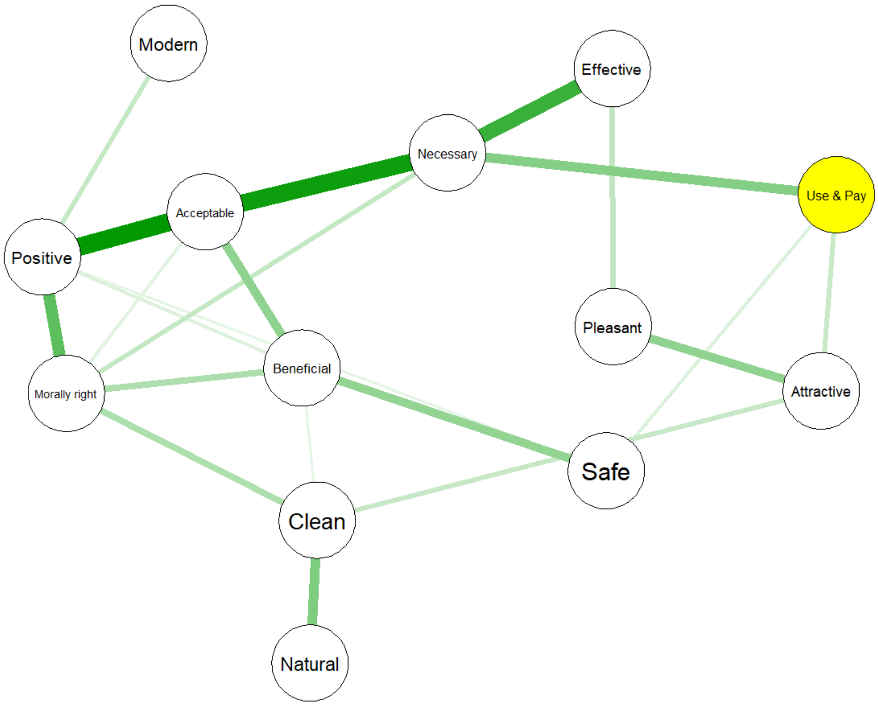
Figure 10 - *PNA Support Intention Adaptation*

Note: *Partial correlations <.1 are not depicted; The thickness of the edges reflects the magnitude of the partial correlation between two nodes; Positive correlations are shown in green, negative in red.*

Subsequently, Network Invariance (*M* = .22; *p* = .18) between the two attitude (acceptability) networks for mitigation and adaptation technologies was tested using an Independent Groups Gaussian Network Comparison Test, revealing no significant differences between the two networks (H1b).

Considering networks related to “Intention to Use & Pay” (Figures 11 and 12), in mitigation technologies (Figure 11) was found that perceiving the technology as “Attractive”, “Necessary”, and “Safe” was connected to “Intention to Use & Pay” (respectively: *r* = 0.14, 95% *CI*: .04, .25; *r* = 0.20, 95% *CI*: .09, .30; *r* = 0.13, 95% *CI*: .03, .23). The other nodes in the network did not show significant connections to “Intention to Use & Pay”.

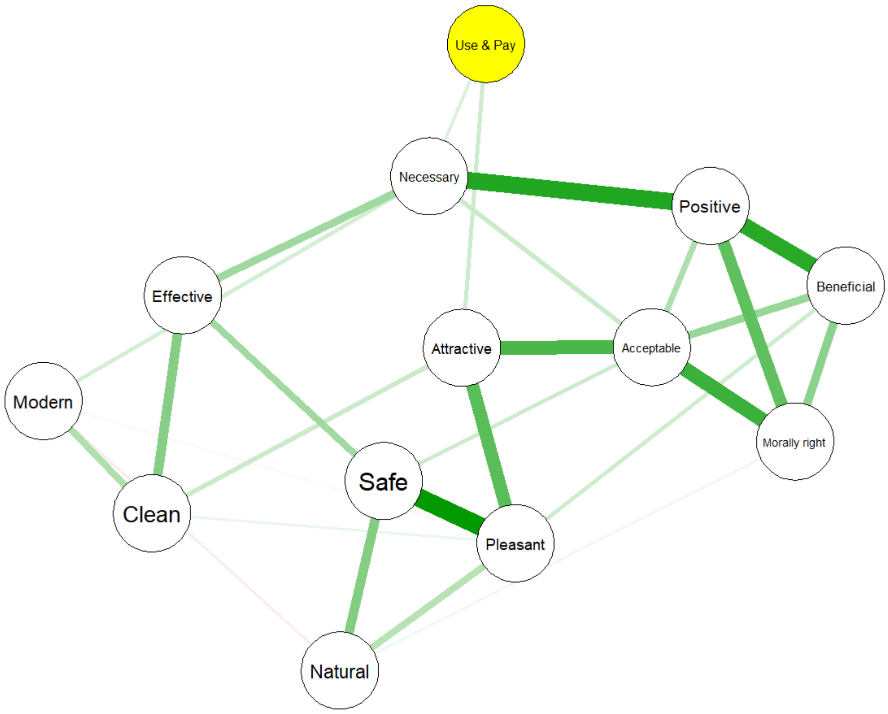
Figure 11 – *PNA Intention to Use & Pay Mitigation*



Note: *Partial correlations <.1 are not depicted; The thickness of the edges reflects the magnitude of the partial correlation between two nodes; Positive correlations are shown in green, negative in red.*

For adaptation technologies (Figure 12), only perceiving the technology as “Necessary” and “Attractive” was found to be connected to “Intention to Use & Pay” (respectively: *r* = 0.12, 95% *CI*: .02, .23; *r* = 0.13, 95% *CI*: .02, .24).

Figure 12 - *PNA Intention to Use & Pay Adaptation*



Note: *Partial correlations <.1 are not depicted; The thickness of the edges reflects the magnitude of the partial correlation between two nodes; Positive correlations are shown in green, negative in red.*

Subsequently, Network Invariance (*M* = .22; *p* = .14) between the two attitude (acceptability) networks for mitigation and adaptation technologies was tested using an Independent Groups Gaussian Network Comparison Test, revealing that the two networks were not significantly different (H1b).

3.4 Discussion

Building on the results of the path model, the study confirmed the central role of normative influence in promoting PEBs, as widely discussed in classical theories (NAT, Schwartz, 1968, 1977; TNC, Cialdini et al., 1990, 1991). Both personal norm and social norms (considered as both injunctive and descriptive) were directly correlated with the acceptability and acceptance of SETs for both mitigation and adaptation (see Perlaviciute & Steg, 2015). Similarly, the study confirms previous findings from the meta-analyses by Milani, Dessi, and Bonaiuto (2024; Study 1), highlighting the primary role of emotional responses to the risks and benefits of the technologies as key drivers of the acceptability and acceptance of SETs (see Cousse 2021; Cousse et al., 2020; Cousse et al., 2021). However, emotional responses to the risks and benefits of SETs were not directly correlated to using or spending money on these technologies. Future research could explore how emotional responses to SETs promote specific behaviors toward these technologies rather than others and investigate which factors turn the emotional responses into action. The study also confirmed the primary and well-established role (e.g., TPB, Ajzen, 1991) - also revealed in the meta-analyses by Milani, Dessi, and Bonaiuto (2024; Study 1) - of attitudes (conceptualized here as acceptability) in promoting behavioral intention (conceptualized here as acceptance) (see also Bamberg & Möser, 2007). Finally, by providing empirical support for the theoretical model developed by Bonaiuto et al. (2024), the study demonstrated the central role of acceptability in mediating the effects of beliefs in promoting acceptance. The structural invariance between the two models further demonstrated the utility of this model in predicting the acceptability and acceptance of both mitigation and adaptation SETs, underscoring the robustness of the model itself.

On the other hand, considering the results from the Gaussian graphical models (PNA), it emerges that, for adaptation SETs, acceptance is primarily driven by the perception of these technologies as necessary. In contrast, a more complex interpretation and perception of acceptability drives the acceptance of mitigation SETs. This could likely be due to the perception of adaptation technologies as distant and not yet strictly necessary, leading those who view them as necessary to be more inclined to accept them. Nevertheless, the invariance between the acceptability networks for mitigation and adaptation SETs suggests that the social acceptance process is grounded in common principles and depends on key characteristics of the technologies, such as their perceived necessity. The study also highlights the utility of graphical approaches (see Bhushan et al., 2019; Zwicker et al., 2020) in conducting exploratory research in environmental psychology, providing critical insights for future studies employing confirmatory approaches.

Finally, considering the average levels of SETs acceptability (see Table 10 and Figure 8) - even when compared to the levels of acceptance - it is evident that they are relatively low. Given the central role of acceptability in the social acceptance process, this suggests the need to focus on improving public perceptions of these technologies. Therefore, specific characteristics of SETs (see paragraph 3.3.3) should be promoted to increase the likelihood of engaging people in sustainable energy behaviors. In summary, future studies should deeply explore how the perception of such technologies influences their adoption and support. Building on the findings related to the first main objective, which confirms the critical role of norms and emotional reactions in shaping the social acceptance of SETs, future research should also investigate how these norms (both social and personal) interact with one another and how the emotional responses may mediate, amplify, or inhibit their effects.

CHAPTER 4

Study 3

4.1 Aim of the study

Building on the theoretical framework outlined in Studies 1 and 2 and the broader literature on the impact of social norms in promoting PEBs (e.g., Schultz et al., 2007), Study 3 focuses on the adopter's beliefs related to the SETs adoption context. Specifically, the impact of social comparison (considered as descriptive social norms) in influencing the social acceptance of SETs is investigated. Given the crucial role of emotional responses in promoting the social acceptance of these technologies (see also Study 1; Milani, Dessi, & Bonaiuto, 2024), Study 3 - following the theoretical framework proposed by Packard and Schultz (2023) - aims to understand the impact of descriptive social norms on individuals' emotional responses and how these, in turn, may guide behavior (see paragraph 1.3). Specifically, building on the theoretical frameworks proposed by the authors, Study 3 focuses on the emotions of contentment and surprise. As previously noted, descriptive norms, by not eliciting immediate social approval or disapproval (Cialdini et al., 1991), may trigger emotional reactions characterized by low arousal or neutral valence.

Surprise, as studied in the literature, arises from violated expectations and uncertain situations (Stavraki et al., 2021). It tends to enhance the processing of surprising information (Reisenzein et al., 2019), potentially motivating individuals to act (see Meyer et al., 1997). Deviations from the norm could thus lead to the perception of violated expectations and uncertainty, prompting individuals to modify their behaviors to align with the norm.

In contrast, contentment, which is associated with the evaluation of goal achievement and the perception of satisfaction (Gilbert et al., 2008; Tong, 2015), may be linked to conforming to a specific norm or perceiving oneself as performing “better” than others about a particular behavior. Unlike the uncertainty tied to surprise, the satisfaction derived from contentment does not encourage behavioral change. Instead, it may result in behavioral deactivation (Lazarus, 1991), leading individuals who perceive themselves as more environmentally responsible than others to reduce their commitment, ultimately conforming to a less pro-environmental norm.

Through two sub-studies (Study 3a, a pilot study, and Study 3b, an experimental study), Study 3 investigates how exposure to others who are more or less pro-environmental (i.e., more or less willing to support SETs) may evoke specific emotional states. Lastly, the study seeks to explore how these emotional states can influence individuals’ behavior, leading them to act in more or less pro-environmental ways (by supporting or not supporting these SETs).

Unlike the previous studies, Study 3 focused solely on mitigation technologies. This decision was based on the findings from Study 2 - and partially from Study 1 (see Section 2.3.1) - which showed that the social acceptance processes for the two SET categories tend to be similar. Therefore, to simplify the process, the study focused on technologies similar to each other that were more familiar to participants and that could be directly adopted. The results of this study could then lead to future research exploring the same effects for adaptation SETs.

4.2 Study 3a (Pilot Study)

4.2.1 Aim

Study 3a (Pilot Study) was designed to achieve two main objectives:

1. The first objective is to investigate the level of knowledge and feasibility of six mitigation technologies (solar, wind, biofuels, hydrogen, tidal, and hydroelectric), which emerged as the most studied in the SSH according to the meta-analyses by

Milani, Dessi, and Bonaiuto (2024; Study 1). This aims to identify, among these six technologies, which is the most well-known and considered the most implementable (feasible) and the least well-known and least implementable. By identifying two technologies with opposing levels of knowledge and feasibility, the subsequent experiment (Study 3b) can be developed to focus on both. Selecting technologies with varying levels of knowledge and feasibility is crucial to demonstrate that normative influence and social comparison affect different technologies, regardless of how familiar people are with them or how feasible they consider them to be.

2. The second objective is to measure the average intention of a sample of Californians (US) to support these mitigation SETs. This information will be used as descriptive normative information in the subsequent experiment (Study 3b).

4.2.2 Method

4.2.2.1 Participants

To be included in the study, participants had to be at least 18 years old, fluent in English, and a U.S. resident from the state of California.

The total sample consisted of 100 participants recruited via Prolific (mean age = 39.16, *sd* = 11.08, min = 21, max = 67). Regarding gender, the sample comprised 48 women (48%) and 52 men (52%).

4.2.2.2 Tool and procedures

The study followed the Ethical Principles of Psychologists and Code of Conduct of the APA. It was approved by the Ethics Committee of Sapienza University of Rome (Approved in September 2024; protocol number: CERT_191A471B182).

Following informed consent for data processing, participants were presented with six information scenarios related to the six mitigation technologies (solar, wind, biofuels, hydrogen, tidal, and hydroelectric), which introduced the technologies by explaining their main pros and cons. The information scenarios presented to participants in Study 3a are detailed in Appendix C. After each information scenario, participants were asked to complete a self-report questionnaire (developed in Qualtrics) containing questions related to the technology presented, encompassing the following measures (also detailed in Appendix C):

- *Subjective Knowledge* (2 items, ad hoc). Participants were presented with two semantic differentials to assess how familiar and knowledgeable they perceived themselves to be regarding the SET (e.g., "*Thinking about XX energy, I feel: Unfamiliar - Familiar*"), with a 7-step response scale.
- *Feasibility* (4 items, ad hoc). Participants were presented with four semantic differentials to assess how "feasible" or implementable, they perceived the SET to be (e.g., "*I think that adopting XX energy is: Difficult - Easy*"), with a 7-step response scale.
- *Support Intention* (8 items, ad hoc). Participants were asked to indicate their willingness to engage in a series of supportive behaviors toward the technology (e.g., "*Considering the following behaviors regarding XX energy, I am willing to: Sign a petition promoting its use*"). Participants were asked to indicate their level of agreement using an 11-point Likert scale (from 0 = "*Not at all*" to 10 = "*Definitely yes*").

4.2.2.3 Data Analysis

Since Study 3a did not have specific hypotheses to test and did not involve analyzing relationships between variables, only descriptive analyses of the examined variables were conducted, focusing on the mean responses to the administered scales. The analyses were performed using *IBM SPSS Statistics 25*.

4.2.3 Results

To identify the mitigation SETs considered the most and least known, as well as those perceived as the most and least implementable (feasible), the mean responses to the "Subjective Knowledge" and "Feasibility" scales for all six examined SETs were analyzed, as reported in Tables 16 and 17.

Table 16 - *Subjective Knowledge descriptives*

	Minimum	**Maximum**	**Mean**	**Std. d.**	**Skewness**	**Kurtosis**
Solar	2.00	7.00	5.69	1.06	-.770	.632
Wind	1.00	7.00	5.15	1.35	-.645	.052
Biofuels	1.00	7.00	3.99	1.62	-.120	-.792
Hydrogen	1.00	7.00	3.65	1.63	.152	-1.026
Tidal	1.00	7.00	3.72	1.69	.026	-.789
Hydroelectric	1.00	7.00	4.27	1.68	-.262	-.787

Table 17 - *Feasibility descriptives*

	Minimum	Maximum	Mean	Std. d.	Skewness	Kurtosis
Solar	1.50	7.00	5.54	1.07	-1.061	1.722
Wind	1.00	7.00	5.29	1.26	-1.392	2.693
Biofuels	1.00	7.00	4.41	1.23	-.331	-.055
Hydrogen	1.00	6.75	4.36	1.15	-.681	.883
Tidal	1.00	7.00	4.52	1.24	-.430	.802
Hydroelectric	1.00	7.00	4.84	1.14	-.807	1.341

The analysis of these mean responses revealed that participants perceived solar energy as the most well-known (M = 5.69) and the most feasible (M = 5.54). In contrast, hydrogen energy was perceived as the least well-known (M = 3.65) and least feasible (M = 4.36).

Subsequently, the mean responses to the “Support Intention” scale were analyzed. These means, which were later used to provide normative feedback in the experimental Study 3b, are reported in Table 18.

Table 18 - *Support Intention descriptives*

	Minimum	Maximum	Mean	Std. d.	Skewness	Kurtosis
Solar	0.13	10.00	5.49	2.54	-.183	-.761
Wind	0.00	10.00	4.81	2.75	-.061	-.862
Biofuels	0.00	9.63	3.60	2.43	.283	-.662
Hydrogen	0.00	10.00	3.89	2.51	.276	-.787
Tidal	0.00	10.00	4.18	2.42	.253	-.532
Hydroelectric	0.00	10.00	4.45	2.64	.029	-.884

In this case, it emerged that solar energy was the technology participants were most willing to support (M = 5.49), while biofuels (M = 3.60) were the technology participants were least willing to support.

4.2.4 Discussion

Based on the analysis of mean responses to the “Subjective Knowledge” and “Feasibility” scales, solar energy (perceived as the most well-known and feasible) and hydrogen energy (perceived as the least well-known and feasible) have been considered for Study 3b. The mean responses to the “Support Intention” scale for these technologies (M = 5.49 for solar energy and M = 3.89 for hydrogen energy) have been used as descriptive normative feedback in Study 3b.

These findings on mean responses also provide a general overview of Californians’ perceptions of the examined mitigation SETs.

4.3 Study 3b (Experimental Study)

The study was pre-registered on OSF (Milani, Schultz, et al., 2024) following the Van’t Veer and Giner-Sorolla (2016) guidelines.

4.3.1 Aim and Hypotheses

Building on the findings from Study 3a, Study 3b aims to experimentally test the effect of descriptive social norms on individuals’ emotional responses and the subsequent impact of these emotional responses on energy-related PEBs (see Section 4.1). The following hypotheses are formulated:

H1: Participants who are less willing to support mitigation energy technologies than their fellow residents (baseline) and who received descriptive normative information (the average response to the technology support intention scale given by their fellow resident during the pilot study) will experience more negative affect (H1a) and more surprise (H1b) than those who have not received descriptive normative information.

H2: Participants who are more willing to support mitigation energy technologies than their fellow residents (baseline) and who received descriptive normative information (the average response to the technology support intention scale given by their fellow residents during the pilot study) will experience more positive affect (H2a) and more contentment (H2b) than those who have not received descriptive normative information.

H3: Participants who are less willing to support mitigation energy technologies than their fellow residents (baseline) and have received descriptive normative information will increase their intention to support the technologies (follow-up) after receiving descriptive normative information (follow-up > baseline) (H3a). No changes in technology support intention are hypothesized in participants who have not received descriptive normative information (follow-up = baseline) (H3b).

In addition, participants who are less willing to support mitigation energy technologies than their fellow resident (baseline) and have received descriptive normative information will have higher follow-up technology support intention than those who have not received descriptive normative information (descriptive normative information > no descriptive normative information) (H3c).

H4: Participants who are more willing to support mitigation energy technologies than their fellow residents (baseline) and have received descriptive normative information will decrease their intention to support the technologies (follow-up) after receiving descriptive normative information (follow-up < baseline) (H4a). No changes in technology support intention are hypothesized in participants who have not received descriptive normative information (follow-up = baseline) (H4b).

In addition, participants who are more willing to support mitigation energy technologies than their fellow residents (baseline) and have received descriptive normative information will have lower follow-up technology support intention than those who have not received descriptive normative information (descriptive normative information < no descriptive normative information) (H4c).

H5: Participants who are less willing to support mitigation energy technologies than their fellow residents (baseline) and who have received descriptive normative information will enact the target behavior (download items) more than those who a have not received descriptive normative information.

H6: Participants who are more willing to support mitigation energy technologies than their fellow residents (baseline) and who have received descriptive normative information will enact the target behavior (download items) less than those who have not received descriptive normative information.

H7: Negative affect will positively mediate the relationship between descriptive normative information (*vs.* no descriptive normative information) and technology support behavior in people who are less willing to support mitigation energy technologies than their fellow residents (baseline).

H8: Positive affect negatively mediates the relationship between descriptive normative information (*vs.* no descriptive normative information) and technology support behavior in people who are more willing to support mitigation energy technologies than their fellow residents (baseline).

H9: Surprise positively mediates the relationship between descriptive normative information (*vs.* no descriptive normative information) and technology support behavior in people who are less willing to support mitigation energy technologies than their fellow residents (baseline).

H10: Contentment negatively mediates the relationship between descriptive normative information (*vs.* no descriptive normative information) and technology support behavior in people who are more willing to support mitigation energy technologies than their fellow residents (baseline).

4.3.2 Method

4.3.2.1 Participants

The total sample consisted of 600 participants recruited via Prolific.

To be included in the study, participants had to be at least 18 years old, fluent in English, a U.S. resident from the state of California, and not have participated in the pilot study (Study 3a).

Participants were exposed (balanced by gender) through double-blind randomization to one of two information scenarios about solar or hydrogen energy (the same scenarios presented in Study 3a). They then completed a questionnaire (developed in Qualtrics) about the technology described in the information scenario they had read.

The "solar" sample comprised 300 participants (mean age = 35.71, *sd* = 12.27, min = 18, max = 70). Concerning gender, the sample consisted of 154 women (51.3 %), 137 men (45.7 %), 9 third gender/non-binary (3.0 %). Regarding the number of participants who were found to be less and more willing to support solar energy than participants in the pilot study (Study 3a), these were respectively 138 (46%) and 162 (54%).

The “hydrogen” sample comprised 300 participants (mean age = 34.72, *sd* = 12.05, min = 18, max = 76). Concerning gender, the sample consisted of 131 women (43.7 %), 163 men (54.3 %), 5 third gender/non-binary (1.7 %), and 1 genderfluid (0.3 %). Regarding the number of participants who were found to be less and more willing to support hydrogen energy than participants in the pilot study (Study 3a), these were respectively 99 (33%) and 201 (67%).

Participants who did not finish the questionnaire, who completed the questionnaire in inadequate time (either too quickly or too slowly) and who failed at least two attention checks were excluded during data collection. Following the data collection phase, participants assigned to the experimental group were excluded from the research if they failed the attention check related to the manipulation.

Only responses from participants who answered all items of the presented measurement scales will be considered, and outliers were included in the analyses.

A total of 611 questionnaires were collected. After eliminating participants according to the above criteria, 600 responses were considered.

4.3.2.2 Tool and procedures

The study followed the Ethical Principles of Psychologists and Code of Conduct of the APA. It was approved by the Ethics Committee of Sapienza University of Rome (Approved in September 2024; protocol number: CERT_191A471B182).

Following informed consent for data processing, research participants were asked to answer a self-report questionnaire (detailed in Appendix C).

Participants were randomly assigned to one of the two selected technologies following the pilot study (Study 3a; solar and hydrogen energy) by double-blind randomization. At this point, participants were presented with an informational technology scenario. A brief introduction to the technology and the main pros and cons were presented (see Appendix C).

Then, through a self-report questionnaire, the intention to support the mitigation energy technologies was measured:

- *Baseline Support Intention* (8 items, ad hoc). Participants were asked to indicate their willingness to adopt a range of supportive behaviors toward the technology (e.g., "*Considering the following behaviors regarding XX energy, I am willing to: Sign a petition promoting its use*"). Participant were asked to indicate their degree of agreement through an 11-level Likert response scale (from 0 = "*Not at all*" to 10 = "*Definitely yes*") (α[3] = .88/.88).

At this point, normative feedback was manipulated (descriptive normative information *vs.* no descriptive normative information).

Some participants (experimental group), after responding to the "Baseline Support Intention" scale, were presented with their average response to the scale and that of the pilot study participants (their fellow residents), including a sentence specifying which of the two averages was the higher (descriptive normative information), as reported in Figure 1C in Appendix C. Other participants (control group) were only be presented with their average response to the scale (no descriptive normative information), as illustrated in Figure 2C in Appendix C. Participants were assigned to one of two groups (experimental or control) by double-blind randomization.

After providing (or not) descriptive normative information, the following variables were measured in the following order:

- *Positive Affect* (10 items, Watson et al., 1988). Participants were asked to think about the information they received, i.e., their own mean response to the "Support Intention"

[3] The two values reported for Cronbach's alpha reflect the measure's reliability within the "solar" and "hydrogen" samples, respectively, before and after the separation bar.

scale or their own mean response to the scale with the mean response of their fellow residents participating in the pilot study. Subsequently, participants were asked to indicate how this impacted their current emotional state (e.g., "*Now, knowing that you are more/less willing to support XX energy than the average Californian, to what extent do you feel each of the following? Proud*") via a 5-level Likert response scale (from 1 = "*Slightly*" to 5 = "*Extremely*") (α = .93/.92).

- *Negative Affect* (10 items, Watson et al., 1988). Participants were asked to think about the information they received, i.e., their own mean response to the "Support Intention" scale or their own mean response to the scale with the mean response of their fellow residents participating in the pilot study. Subsequently, participants were asked to indicate how this impacted their current emotional state (e.g., "*Now, knowing that you are more/less willing to support XX energy than the average Californian, to what extent do you feel each of the following? Ashamed*") via a 5-level Likert response scale (from 1 = "*Slightly*" to 5 = "*Extremely*") (α = .89/.89).
- *Surprise* (1 item, ad hoc). Participants were asked to think about the information they received, i.e., their own mean response to the "Support Intention" scale or their own mean response to the scale with the mean response of their fellow residents participating in the pilot study. Subsequently, participants were asked to indicate how this impacted their current emotional state (i.e., "*Now, knowing that you are more/less willing to support XX energy than the average Californian, to what extent do you feel Surprise?*") via a 5-level Likert response scale (from 1 = "*Slightly*" to 5 = "*Extremely*").
- *Contentment* (1 item, ad hoc). Participants were asked to think about the information they received, i.e., their own mean response to the "Support Intention" scale or their own mean response to the scale with the mean response of their fellow residents participating in the pilot study. Subsequently, participants were asked to indicate how

this impacted their current emotional state (i.e., "*Now, knowing that you are more/less willing to support XX energy than the average Californian, to what extent do you feel Content?*") via a 5-level Likert response scale (from 1 = "*Slightly*" to 5 = "*Extremely*").

- *Follow-up Support Intention* (8 items, ad hoc). Participants were asked again to answer the questions proposed in the "Baseline Support Intention" scale (α = .91/.90).
- *Support Behavior* (1 item, ad hoc). Participants were asked to download (or not) a series of articles (1 to 4) containing information covering different topics (e.g., "*What is XX energy and why it is needed*") related to the considered technology. The question corresponds to 5 response options, i.e., download no article or download the proposed articles. Participants will be given multiple response options to download more than one article if interested. There will then be a continuous variable from 0 (no article downloaded) to 4 (4 articles downloaded).

4.3.2.3 Data Analysis

For hypotheses H1, H2, H5, and H6, the analytical approach deviated from the original preregistration (Milani, Schultz, et al., 2024), opting for a 2x2x2 factorial design to test these hypotheses. This approach was chosen to explore the potential interaction effects among various factors. Nonetheless, the results from both approaches remain consistent. To investigate the effects of normative feedback (descriptive social norms) on emotional responses ("Positive Affect", "Negative Affect", "Surprise", "Contentment") and "Support Behavior" (hypotheses 1, 2, 5, and 6), a series of 2 normative feedbacks (descriptive normative information *vs.* no descriptive normative information) x2 "Baseline Support Intention" average (above *vs.* below pilot average) x2 "Technology" (solar *vs.* hydrogen) factorial ANOVAs were conducted.

This approach allowed us to explore how normative feedback impacts emotional states and technology support behavior, and how these effects vary depending on participants' "Baseline Support Intention" average, and "Technology". Pairwise comparisons were conducted where significant main effects and interactions were found to explore differences between groups.

The sample size needed to test the 2x2x2 ANOVAs (hypotheses 1, 2, 5, and 6) was estimated through G*Power v3.1.9.7 software (Faul et al., 2007), considering a small effect size (related to the variance explained by the tested model) through a conservative approach. Thus, assuming a small effect size (f^2 = .02), statistical power set at .80, critical alpha set at .05, considering 8 groups, and 1 numerator degrees of freedom, the software suggests a minimum sample size of 403 participants.

For hypotheses H3 and H4, the analytical approach deviated from the original preregistration (Milani, Schultz, et al., 2024), opting for a 2x2x2x2 mixed factorial design to test these hypotheses. This approach was chosen to explore also the potential interaction effects of the "Technology" factor. Nonetheless, the results from both approaches remain consistent.

To analyze changes in technology support intention over time and how these changes are caused by normative feedback and "Baseline Support Intention" (hypotheses 3 and 4), a 2x2x2x2 mixed-factorial ANOVA was employed, with time (baseline *vs.* follow-up support intention) as within-subjects factor, and normative feedback (descriptive normative information *vs.* no descriptive normative information), "Baseline Support Intention" average (above *vs.* below pilot average), and "Technology" (solar *vs.* hydrogen) as between-subjects factors. This mixed-design approach was useful to investigate the within-subjects' effects (changes in technology support intention from baseline to follow-up) and the between-subject's effects (differences in "Follow-up Support Intention" across the groups). This was assessed to determine how normative feedback influences changes in technology support intention over time and how the “Baseline Support Intention” average and “Technology” moderate these effects.

The sample size needed to test the 2x2x2x2 mixed-factorial ANOVA (hypotheses 3 and 4) was estimated through G*Power v3.1.9.7 software (Faul et al., 2007), considering a small effect size (related to the variance explained by the tested model) through a conservative approach. Thus, assuming a small effect size (f^2 = .04), statistical power set at .80, and critical alpha set at .05, considering 8 groups, two measurements, and correlation among repeated measures of .5, the software suggests a minimum sample size of 104 participants.

To test whether emotional responses (“Positive Affect”, “Negative Affect”, “Surprise”, “Contentment”) mediate the relationship between descriptive normative information and technology “Support Behavior” (hypotheses 7, 8, 9, and 10), mediation analyses were conducted. Linear regression models were used to explore these mediating relationships, and bootstrapping methods were applied to assess the significance of indirect effects, with 95% confidence intervals and 10000 bootstrapping iterations. Mediation analyses were conducted separately for participants with different “Baseline Support Intention” (above *vs.* below pilot average). Based on the different “Baseline Support Intention” averages, the models included different mediators (see paragraph 4.3.1).

The sample size needed to test mediation hypotheses (7, 8, 9, and 10) was estimated through Monte Carlo simulation using the statistical tool by Schoemann et al. (2017), estimating a medium effect (r = .30) following Cohen’s guidelines (1992) for the relationship between all variables in the model with 5000 Power Analysis Replications (20000 Monte Carlo Draws for Replications), and a confidence level of 95%. The minimum required sample size to achieve a power of .80 in estimating the indirect effect is 150 participants. Considering that hypotheses 7, 8, 9, and 10 were tested on 4 separate groups of participants taking into account 2 energy technologies (solar and hydrogen) x 2 “Baseline Support Intention” average (above *vs.* below pilot average), the sample needed to test all four hypotheses was 150*4 = 600 participants.

Because the sample needed to test mediation hypotheses was also sufficient to test the other hypotheses, data were collected from 600 participants (the higher sample size required).

The analyses were performed using *IBM SPSS Statistics 25*, and to test hypotheses 7, 8, 9, and 10, the *PROCESS v4.2* macro by Andrew F. Hayes was used (see Hayes, 2017). The *R* (version 4.3.3) packages “boot” (version 1.3-31) and “emmeans” (version 1.10.4) were used to assess heteroskedasticity and normality violation - through a parametric bootstrapped approach - in testing hypotheses 1, 2, 5, and 6.

4.3.3 Results

4.3.3.1 Descriptive statistics

Table 19 shows the descriptive statistics of the measured variables used to test the solar and hydrogen energy hypotheses.

Variables generally followed a normal distribution, reporting acceptable values of skewness and kurtosis (< 2; Garson, 2012; Field, 2009; Lomax & Hahs-Vaughn, 2012), except for the “Negative Affect” measure in both the “Solar energy” and the “Hydrogen energy” samples, which exhibited extremely high skewness (s = 2.40; s = 2.69) and kurtosis (k = 6.09; k = 8.60), indicating reduced variability and severely violating the assumption of univariate normality.

Table 19 - *Descriptive statistics*

	Minimum	Maximum	Mean	Std. d.	Skewness	Kurtosis
Negative Affect	1.00 / 1.00	3.50 / 3.50	1.26 / 1.25	.45 / .42	2.40 / 2.69	6.09 / 8.60
Positive Affect	1.00 / 1.00	5.00 / 5.00	2.63 / 2.42	1.01 / .90	.39 / .60	-.73 / -.16
Surprise	1.00 / 1.00	5.00 / 5.00	1.92 / 1.88	1.14 / 1.08	1.04 / 1.14	.04 / .54
Contentment	1.00 / 1.00	5.00 / 5.00	2.69 / 2.50	1.21 / 1.21	.17 / .32	-.82 / -.82
Baseline Support Intention	0.00 / 0.00	10.00 / 10.00	5.45 / 4.63	2.09 / 1.92	-.44 / -.01	-.14 / -.31
Follow-up Support Intention	0.00 / 0.00	10.00 / 10.00	5.15 / 4.16	2.36 / 2.14	-.28 / .17	-.56 / -.54
Support Behavior	0.00 / 0.00	4.00 / 4.00	0.77 / 1.04	1.28 / 1.46	1.50 / 1.13	.91 / -.24

Note: *Descriptive statistics presented before the separation bar refer to Solar energy, those presented after the bar refer to Hydrogen energy.*

4.3.3.2 Hypotheses testing

Below, the effects of descriptive norm on the various DVs are reported.

4.3.3.2.1 Direct effects of the descriptive norm on emotional reactions

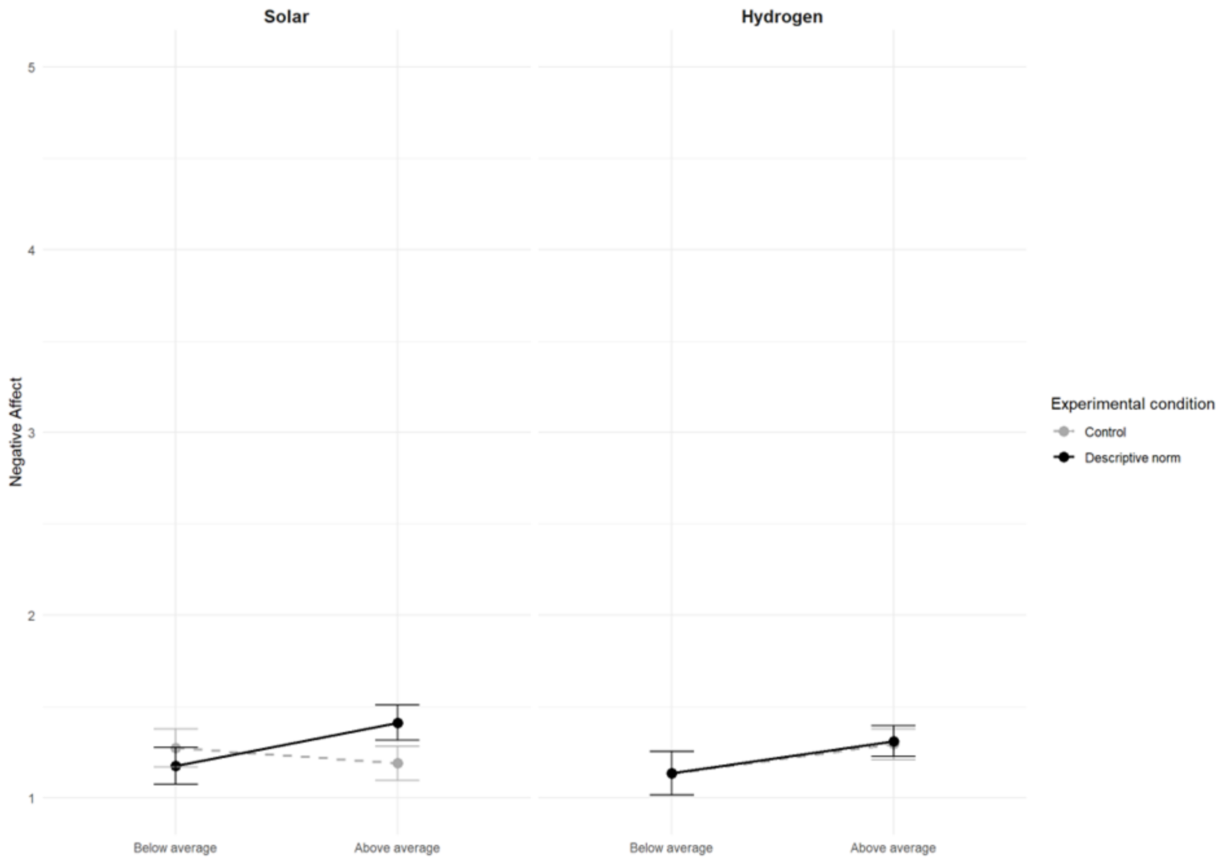
Regarding H1a, since "Negative Affect" showed a severe violation of univariate normality (see paragraph 4.3.3.1), it was not possible to conduct a traditional ANOVA. Additionally, as heteroskedasticity (violation of variance homogeneity) was also identified through Levene's test ($F_{(7, 592)} = 7.01$, $p < .001$), ANOVA with parametric bootstrapped p-values for main effects and interactions, and bootstrapped pairwise comparison were used to assess heteroskedasticity and normality violation.

The 2x2x2 ANOVA on "Negative Affect" revealed a significant main effect for "Baseline Support Intention" average ($F_{(1, 592)} = 10.36$, $p < .001$, $\omega^2 = .017$), with participants above average perceiving more "Negative Affect" ($M = 1.30$, $SE = .02$, $n = 363$ *vs*. below $M = 1.18$, *SE* = .03, *n* = 237). “Experimental condition” ($F_{(1, 592)}$ = 1.39, *p* = .216, ω^2 = .000) and “Technology” ($F_{(1, 592)}$ = .76, *p* = .341, ω^2 = .001) did not show significant main effects.

Considering interaction effects, the “Baseline Support Intention” average X “Experimental condition” interaction was significant ($F_{(1, 592)}$ = 5.18, *p* = .022, ω^2 = .007). Specifically, among participants below average, no significant differences emerged due to the descriptive norm (*M* = 1.15, *SE* = .03, *n* = 122 *vs*. control *M* = 1.20, *SE* = .04, *n* = 115; *MD* = -.05, *SE* = .06, *95% CI* [-.16, .06]). On the other hand, significant differences emerged due to the descriptive norm among participants above average (*M* = 1.36, SE = .03, *n* = 178 *vs*. control *M* = 1.24, *SE* = .03, *n* = 185; *MD* = .12, *SE* = .05, *95% CI* [.03, .21]). In contrast, the “Technology” X “Experimental condition” ($F_{(1, 592)}$ = 1.55, *p* = .200, ω^2 = .001), and “Technology” X “Baseline Support Intention” average ($F_{(1, 592)}$ = 1.55, *p* = .226, ω^2 = .001) interactions did not reach significance. Finally, the “Baseline Support Intention” average X “Technology” X “Experimental condition” three-way interaction was significant ($F_{(1, 592)}$ = 4.50, *p* = .029, ω^2 = .006). Precisely, in participants above average, regarding solar energy a significant difference was found between participants in the descriptive norm condition and those in the control condition (*MD* = .22, *SE* = .07, *95% CI* [.09, .39]), while no difference was found regarding hydrogen energy (*MD* = .02, *SE* = .06, *95% CI* [-.11, .15]).

Testing the hypothesized difference in participants below the average (descriptive norm > control), no significant effect was found for solar (*MD* = -.10, *SE* = .07, *95% CI* [-.24, .02]) and hydrogen (*MD* = .003, *SE* = .09, *95% CI* [-.09, .11]) energies, thus leading to a rejection of H1a. Follow-up pairwise comparisons highlighted several significant effects that were not hypothesized. Considering solar energy, participants in the descriptive norm condition with above-average scores showed a significant difference compared to those with below-average scores (*MD* = .24, *SE* = .07, *95% CI* [.10, .39]). Considering hydrogen energy, a significant difference was found in participants in the control condition with above-average scores compared to those with below-average scores (*MD* = .16, *SE* = .07, *95% CI* [.05, .27]) and participants in the descriptive norm condition with above-average scores compared to those with below-average scores (*MD* = .17, *SE* = .07, *95% CI* [.05, .30]). This pattern of results is shown in Figure 13.

Figure 13 - *Negative Affect Estimated Marginal Means*



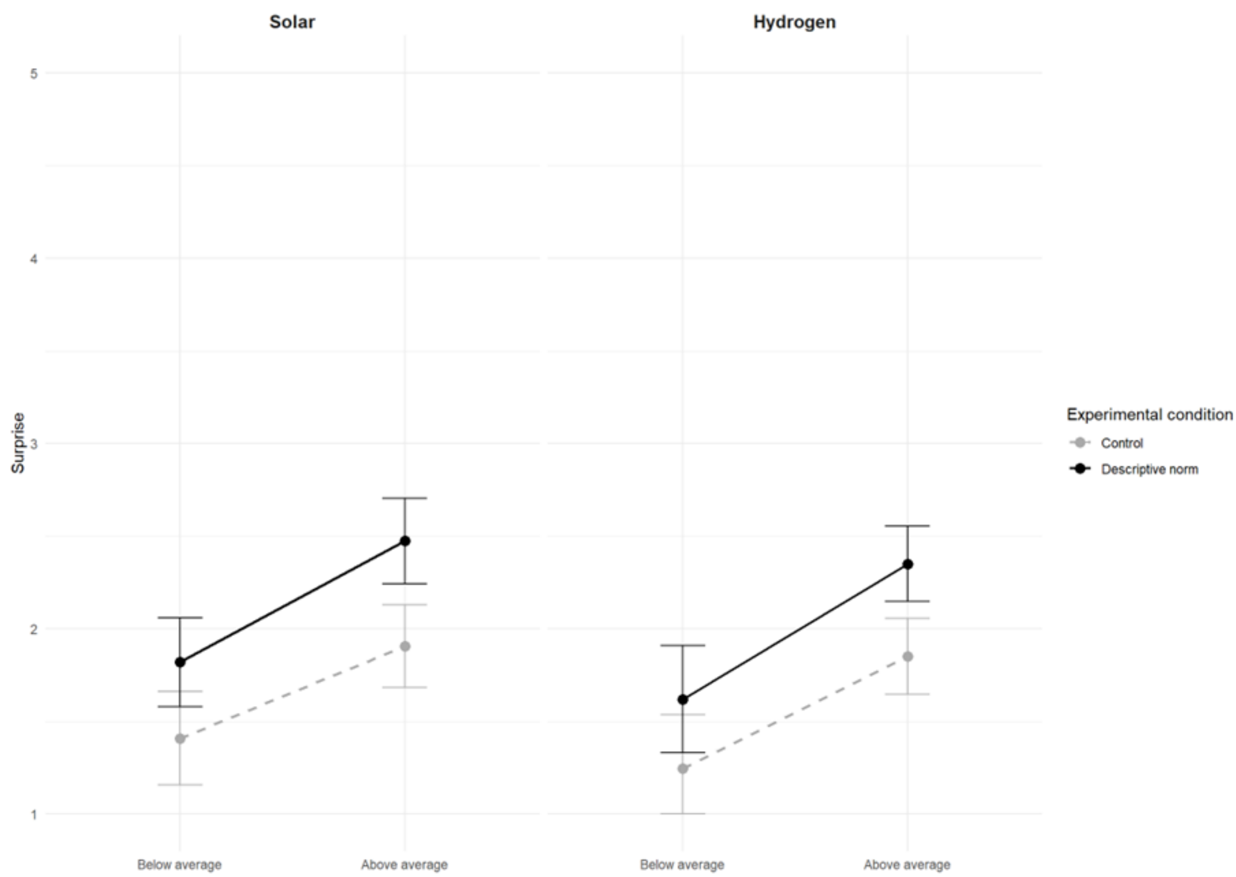
Regarding H1b, given that heteroskedasticity was observed through Levene's test ($F_{(7, 592)}$ = 11.435, p < .001), ANOVA with parametric bootstrapped p-values for main effects and interactions, and bootstrapped pairwise comparison were used to assess heteroskedasticity.

The 2x2x2 ANOVA on "Surprise" revealed a significant main effect for "Baseline Support Intention" average ($F_{(1, 592)}$ = 47.67, p < .001, ω^2 = .072), with participants above average perceiving more “Surprise” (*M* = 2.15, *SE* = .06, *n* = 363 *vs*. below *M* = 1.52, *SE* = .07, *n* = 237). A significant main effect of the “Experimental condition” also emerged ($F_{(1, 592)}$ = 29.53, p < .001, ω^2 = .040), with participants in the descriptive norm condition perceiving more “Surprise” (*M* = 2.07, *SE* = .06, *n* = 300 *vs*. control *M* = 1.60, *SE* = .06, *n* = 300). “Technology” ($F_{(1, 592)}$ = 2.07, p = .154, ω^2 = .002) did not show a significant main effect.

Considering interaction effects, all interactions, namely the “Baseline Support Intention” average X “Experimental condition” ($F_{(1, 592)}$ = .59, p = .390, ω^2 = .001), “Technology” X “Experimental condition” ($F_{(1, 592)}$ = .12, p = .462, ω^2 = .001), and “Technology” X “Baseline Support Intention” average ($F_{(1, 592)}$ = .28, p = .494, ω^2 = .001) two-way interactions, and the “Baseline Support Intention” average X “Technology” X “Experimental condition” three-way interaction ($F_{(1, 592)}$ = .01, p = .503, ω^2 = .001) were not significant. Testing the hypothesized difference in participants below the average (descriptive norm > control), a significant effect was found for solar (*MD* = .41, *SE* = .18, *95% CI* [.11, .70]) and hydrogen (*MD* = .38, *SE* = .21, *95% CI* [.09, .62]) energies, supporting H1b, as shown in Figure 14.

Moreover, pairwise comparisons highlighted several significant effects that were not hypothesized. Considering solar energy, a significant difference was found in participants above average between participants in the descriptive norm condition and those in the control condition (*MD* = .57, *SE* = .16, *95% CI* [.18, .89]). Additionally, participants in the control condition with above-average scores showed a significant difference compared to those with below-average scores (*MD* = .50, *SE* = .17, *95% CI* [.16, .82]), and participants in the descriptive norm condition with above-average scores showed a significant difference compared to those with below-average scores (*MD* = .65, *SE* = .17, *95% CI* [.28, 1.01]). Considering hydrogen energy, a significant difference was found in participants above average between participants in the descriptive norm condition and those in the control condition (*MD* = .50, *SE* = .15, *95% CI* [.17, .81]). Additionally, participants in the control condition with above-average scores showed a significant difference compared to those with below-average scores (*MD* = .61, *SE* = .18, *95% CI* [.34, .87]), and participants in the descriptive norm condition with above-average scores showed a significant difference compared to those with below-average scores (*MD* = .73, *SE* = .18, *95% CI* [.40, 1.04]).

Figure 14 - *Surprise Estimated Marginal Means*



Regarding H2a, given that heteroskedasticity was observed through Levene's test ($F_{(7, 592)}$ = 4.459, p < .001), ANOVA with parametric bootstrapped p-values for main effects and interactions, and bootstrapped pairwise comparison were used to assess heteroskedasticity.

The 2x2x2 ANOVA on "Positive Affect" revealed a significant main effect for "Baseline Support Intention" average ($F_{(1, 592)} = 149.93$, $p < .001$, $\omega^2 = .208$), with participants above average perceiving more "Positive Affect" ($M = 2.89$, $SE = .04$, $n = 363$ *vs*. below $M = 1.98$, $SE = .06$, $n = 237$). A significant main effect of "Technology" also emerged ($F_{(1, 592)} = 21.84$, $p < .001$, $\omega^2 = .023$), with participants responding to questions about solar energy reporting more "Positive Affect" ($M = 2.59$, $SE = .05$, $n = 300$ *vs*. hydrogen $M = 2.28$, $SE = .05$, $n = 300$). The "Experimental condition" ($F_{(1, 592)} = .88$, $p = .297$, $\omega^2 = .001$) did not show a significant main effect.

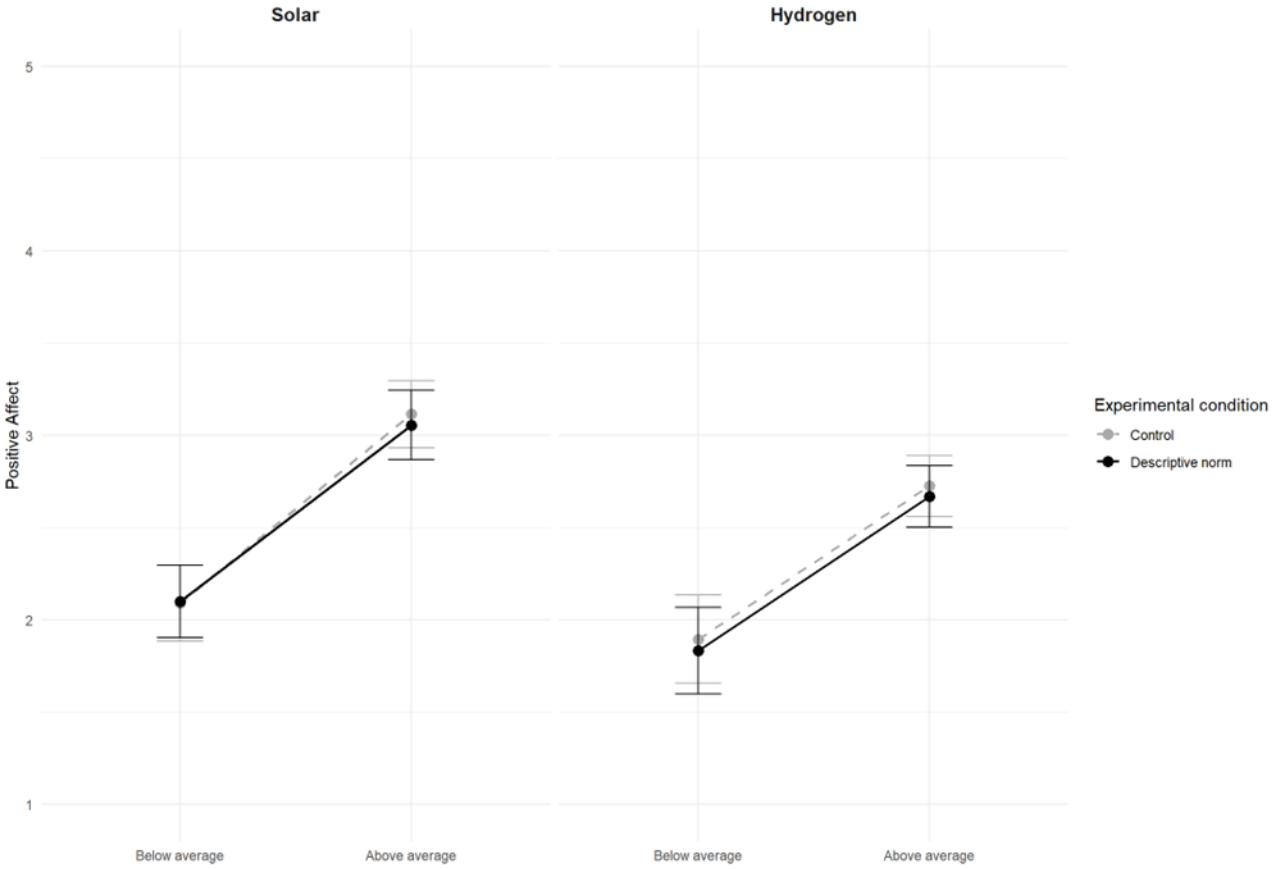
Considering interaction effects, all interactions, namely the "Baseline Support Intention" average X "Experimental condition" ($F_{(1, 592)} =.06$, $p = .484$, $\omega^2 = .001$), "Technology" X "Experimental condition" ($F_{(1, 592)} = .03$, $p = .465$, $\omega^2 = .001$), and "Technology" X "Baseline Support Intention" average ($F_{(1, 592)} = 1.18$, $p= .264$, $\omega^2 = .000$) two-way interactions, and the "Baseline Support Intention" average X "Technology" X "Experimental condition" three-way interaction ($F_{(1, 592)} = .07$, $p = .535$, $\omega^2 = .001$) were not significant.

Testing the hypothesized difference in participants above the average (descriptive norm > control), no significant effect was found for solar ($MD = -.06$, $SE = .13$, *95% CI* [-.36, .23]) and hydrogen ($MD = -.06$, $SE = .12$, *95% CI* [-.31, .20]) energies, thus leading to a rejection of H2a, as shown in Figure 15.

Pairwise comparisons, then, highlighted several significant effects that were not hypothesized. Considering solar energy, participants in the control condition with above-average scores showed a significant difference compared to those with below-average scores ($MD = 1.02$, $SE = .14$, *95% CI* [.72, 1.32]), and participants in the descriptive norm condition with above-average scores showed a significant difference compared to those with below-average scores ($MD = .96$, $SE = .14$, *95% CI* [.69, 1.23]). Considering hydrogen energy, participants in the control condition with above-average scores showed a significant difference compared to those with below-average scores (*MD* = .83, *SE* = .15, *95% CI* [.57, 1.08]), and participants in the descriptive norm condition with above-average scores showed a significant difference compared to those with below-average scores (*MD* = .84, *SE* = .15, *95% CI* [.58, 1.08]).

Additionally, with a "Technology" effect emerging, comparisons were made between the same groups across different technologies. Notably, significant differences were observed between solar and hydrogen energies among participants with above-average scores in the descriptive norm condition (*MD* = .39, *SE* = .13, *95% CI* [.12, .66]), and among those with above-average scores in the control condition (*MD* = .39, *SE* = .13, *95% CI* [.12, .67]). Significant differences were also found among participants with below-average scores in the descriptive norm condition (*MD* = .27, *SE* = .16, *95% CI* [.04, .49]). In contrast, no significant differences were detected among participants with below-average scores in the control condition (*MD* = .20, *SE* = .16, *95% CI* [-.04, .45]).

Figure 15 - *Positive Affect Estimated Marginal Means*



Regarding H2b, given that homoskedasticity was observed through Levene's test ($F_{(7, 592)}$ = 1.506, p = .162), ANOVA of main effects and interactions and pairwise comparison were performed.

The 2x2x2 ANOVA on "Contentment" revealed a significant main effect for "Baseline Support Intention" average ($F_{(1, 592)}$ = 24.99, p < .001, ηp^2 = .041), with participants above the average perceiving more "Contentment" (M = 2.80, SE = .06, n = 363 *vs*. below M = 2.30, SE = .08, n = 237). A significant main effect of "Technology" also emerged ($F_{(1, 592)}$ = 5.24, p = .022, ηp^2 = .009), with participants answering questions about solar energy reporting more "Contentment" (M = 2.66, SE = .07, n = 300 *vs*. hydrogen M = 2.43, SE = .07, n = 300). The

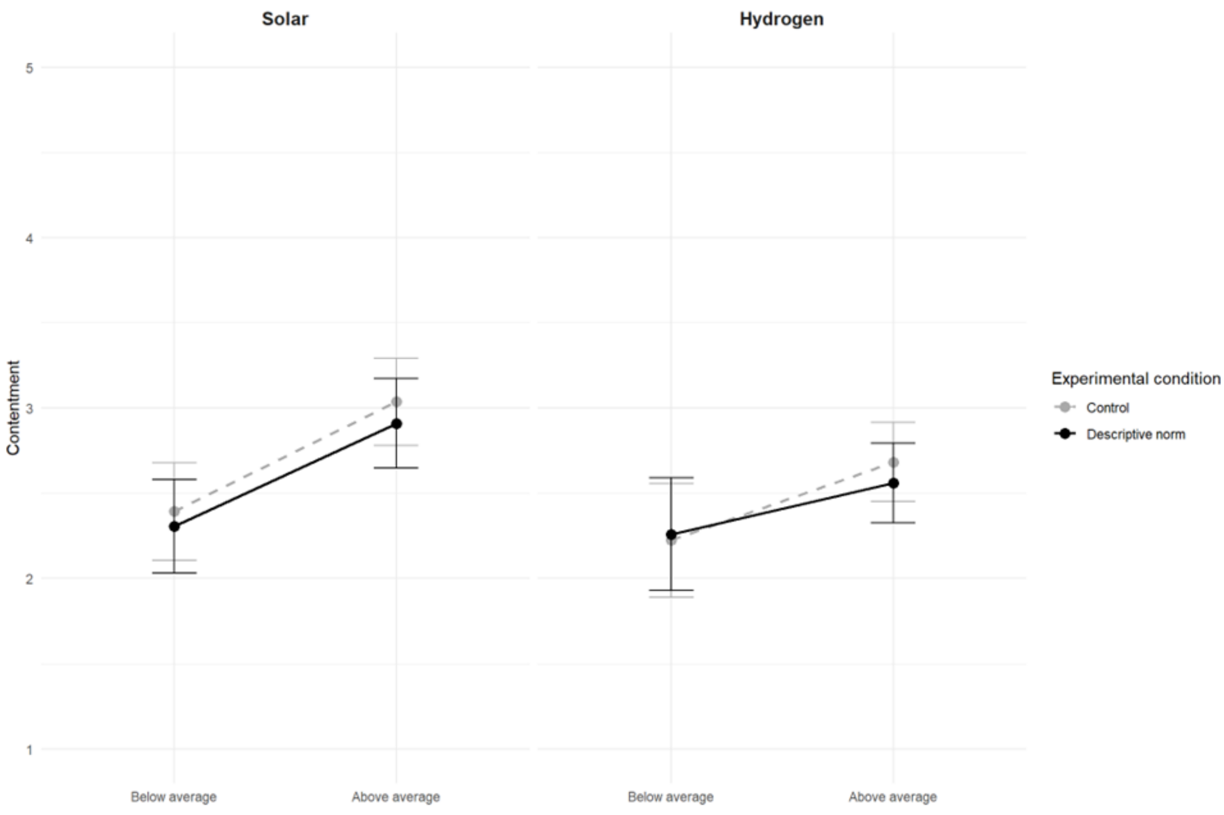
"Experimental condition" ($F_{(1, 592)}$ = .57, p = .453, ηp^2 = .001) did not show a significant main effect.

Considering interaction effects, all interactions, namely the "Baseline Support Intention" average X "Experimental condition" ($F_{(1, 592)}$ = .24, p = .626, ηp^2 =.000), "Technology" X "Experimental condition" ($F_{(1, 592)}$ = .10, p = .753, ηp^2 = .000), and "Technology" X "Baseline Support Intention" average ($F_{(1, 592)}$ = 1.48, p = .224, ηp^2 = .002) two-way interactions, and the "Baseline Support Intention" average X "Technology" X "Experimental condition" three-way interaction ($F_{(1, 592)}$ = .09, p = .762, ηp^2 = .000) were not significant. Pairwise comparisons with Bonferroni correction compared the means between groups to limit the family-wise error rate. Testing the hypothesized difference in participants above the average (descriptive norm> control), no significant effect was found for solar (*MD* = -.09, *SE* = .20, *95% CI* [-.49, .31]) and hydrogen (*MD* = .04, *SE* = .24, *95% CI* [-.43, .50]) energies, thus leading to a rejection of H2b, as shown in Figure 16 below.

Moreover, pairwise comparisons highlighted several significant effects that were not hypothesized. Considering solar energy, participants in the control condition with above-average scores showed a significant difference compared to those with below-average scores (*MD* = .64, *SE* = .20, *95% CI* [.26, 1.03]), and participants in the descriptive norm condition with above-average scores showed a significant difference compared to those with below-average scores (*MD* = .61, *SE* = .19, *95% CI* [.22, .99]). Considering hydrogen energy, participants in the control condition with above-average scores showed a significant difference compared to those with below-average scores (*MD* = .46, *SE* = .21, *95% CI* [.05, .87]). In contrast, no significant difference was found in participants in the descriptive norm condition with above-average scores compared to those with below-average scores (*MD* = .30, *SE* = .21, *95% CI* [-.10, .70]). Additionally, since a "Technology" effect was observed, comparisons between solar and hydrogen energies across different groups were conducted.

Notably, a significant difference emerged between solar and hydrogen energies among participants with above-average scores in the control condition (*MD* = .35, *SE* = .18, *95% CI* [.01, .70]). However, no significant differences were found among participants with above-average scores in the descriptive norm condition (*MD* = .35, *SE* = .18,*95% CI* [-.002, .70]), and among participants with below-average scores in either the descriptive norm condition (*MD* = .05, *SE* = .22, *95% CI* [-.38, .48]) and the control condition (*MD* = .17, *SE* = .22, *95% CI* [-.27, .61]).

Figure 16 - *Contentment Estimated Marginal Means*



4.3.3.2.2 Direct effects of the descriptive norm on support intention and behavior

Regarding H3 and H4, considering within-subjects effects, the 2x2x2x2 mixed ANOVA revealed a significant main effect of time ($F_{(1, 592)}$ = 130.83, p < .001, ηp^2 = .181), suggesting that the average scores on the support intention scale decreased significantly over time (*MD* = -.40, *SE* = .04, *95% CI* [-.47, -.33]). The interaction between time and "Baseline Support Intention" average was significant ($F_{(1, 592)}$ = 8.92, p = .003, ηp^2 = .015), indicating that the effect of time varied according to the level of "Baseline Support Intention" (above *vs*. below the pilot average). Specifically, the results show that support intention decreased more over time among participants below the average (*MD* = -.51, *SE* = .06, *95% CI* [-.61, -.40]) than among participants above average (*MD* = -.30, *SE* = .04, *95% CI* [-.38, -.21]). Moreover, the interaction between time and "Technology" was significant ($F_{(1, 592)}$ = 6.74, p = .010, ηp^2 = .011), indicating that the effect of time varied according to the specific energy technology (solar and hydrogen). Specifically, the results show that support intention decreased more over time regarding hydrogen energy (*MD* = -.49, *SE* = .05, *95% CI* [-.59, -.39]) than solar energy (*MD* = -.31, *SE* = .05, *95% CI* [-.41, -.22]). On the other hand, the interaction between time and the descriptive norm was not significant ($F_{(1, 592)}$ = .00, p = 1.00, ηp^2 = .000), suggesting that the experimental condition did not influence changes over time. three-way and four-way interactions also do not reach significance.

Testing the hypothesized differences in participants below average, a significant decrease over time emerged in participants in the descriptive norm condition both regarding solar (*MD* = -.35, *SE* = .10, *95% CI* [-.54, -.16]) and hydrogen (*MD* = -.66, *SE* = .12, *95% CI* [-.89, -.43]) energies, thereby rejecting H3a. Similarly, in participants below the average emerged a significant decrease over time in participants in the control condition both regarding solar (*MD* = -.56, *SE* = .10, *95% CI* [-.76, -.36]) and hydrogen (*MD* = -.45, *SE* = .12, *95% CI* [-.69, -.22]) energies, thereby rejecting H3b.

Testing the hypothesized differences in participants above the average does not show a significant decrease over time in participants in the descriptive norm condition regarding solar energy (*MD* = -.18, *SE* = .09, *95% CI* [-.37, .002]), while did emerge regarding hydrogen energy (*MD* = -.41, *SE* = .08, *95% CI* [-.58, -.25]), thereby partially confirming H4a. On the other hand, in participants above the average emerged a significant decrease over time in participants in the control condition both regarding solar (*MD* = -.15, *SE* = .09, *95% CI* [-.32, .03]) and hydrogen (*MD* = -.44, *SE* = .08, *95% CI* [-.61, -.28]) energies, thereby rejecting H4b (see Figure 17).

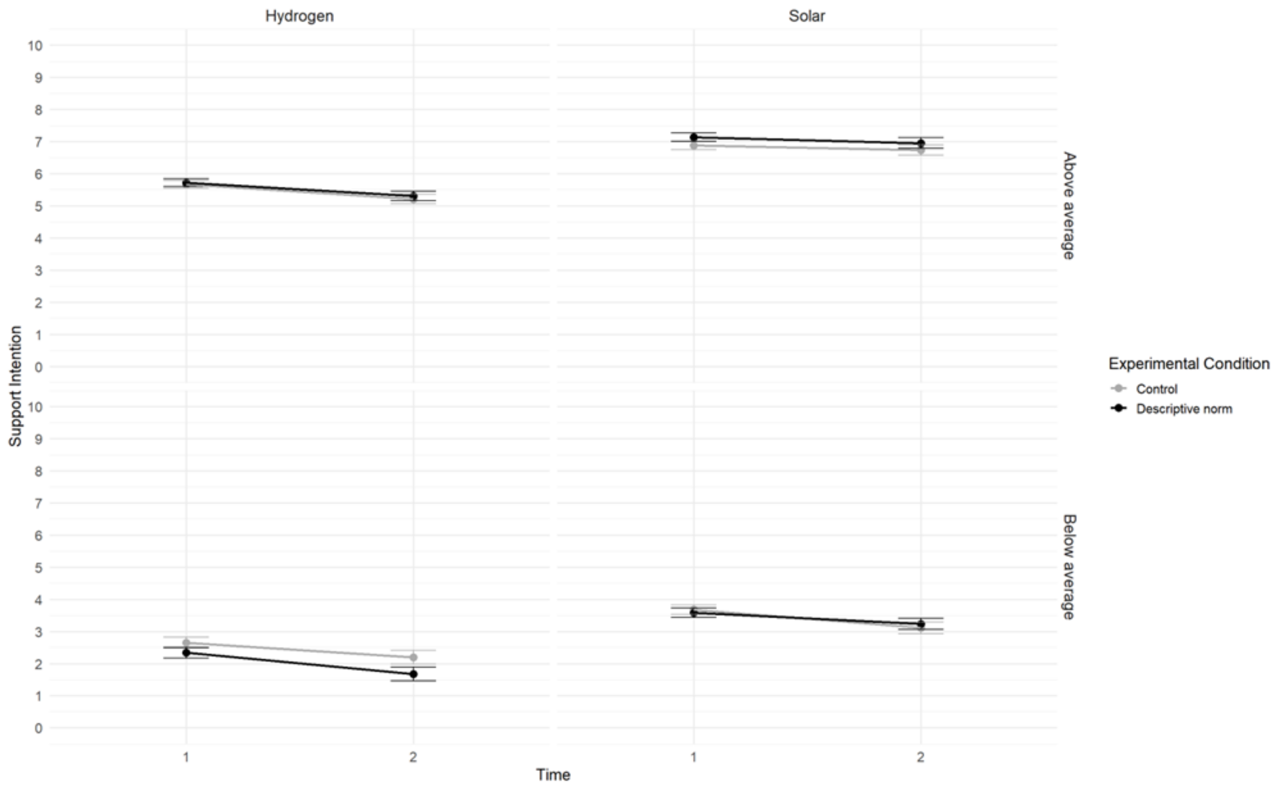
Considering between-subject effects, significant effects of "Baseline Support Intention" average ($F_{(1, 592)}$ = 978.46, p < .001, ηp^2 = .623) and "Technology" ($F_{(1, 592)}$ = 147.31, p < .001, ηp^2 = .199) were observed on "Follow-up Support Intention". The results highlight the consistency of support intention over time and confirm findings from the pilot study, showing that participants are more inclined to support solar energy than hydrogen energy (*MD* = 1.32, *SE* = .11, *95% CI* [1.10, 1.53]). However, no effect of the "Experimental condition" on "Follow-up Support Intention" was found ($F_{(1, 592)}$ = .04, p = .848, ηp^2 = .000).

Two-way and three-way interactions also do not reach significance.

Testing the hypothesized differences in participants below the average, no significant difference was found between descriptive norm and control condition both regarding solar (*MD* = .01, *SE* = .22, *95% CI* [-.42, .44]) and hydrogen (*MD* = -.41, *SE* = .26, *95% CI* [-.92, .10]) energies, thereby rejecting H3c.

Testing the hypothesized differences in participants above the average, no significant difference was found between descriptive norm and control condition both regarding solar (*MD* = .24, *SE* = .20, *95% CI* [-.16, .64]) and hydrogen (*MD* = .08, *SE* = .18, *95% CI* [-.28, .43]) energies, thereby rejecting H4c.

Figure 17 - *Support Intention variation over time*



Regarding H5 and H6, given that heteroskedasticity was observed through Levene's test ($F_{(7, 592)}$ = 5.793, p = .000), ANOVA with parametric bootstrapped p-values for main effects and interactions, and bootstrapped pairwise comparison were used to assess heteroskedasticity.

The 2x2x2 ANOVA on "Support Behavior" revealed a significant main effect for "Baseline Support Intention" average ($F_{(1, 592)}$ = 18.96, p < .001, ω^2 = .025), with participants above the average engaging more in "Support Behavior" (M = 1.09, SE = .07, n = 363 *vs*. below M = .62, SE = .09, n = 237). "Experimental condition" ($F_{(1, 592)}$ = .13, p = .443, ω^2 = .001) and "Technology" ($F_{(1, 592)}$ = 3.40, p = .076, ω^2 = .003) did not reported significant main effects.

Considering interaction effects, all interactions, namely the "Baseline Support Intention" average X "Experimental condition" ($F_{(1, 592)}$ = 3.06, p = .077, ω^2 = .003), "Technology" X

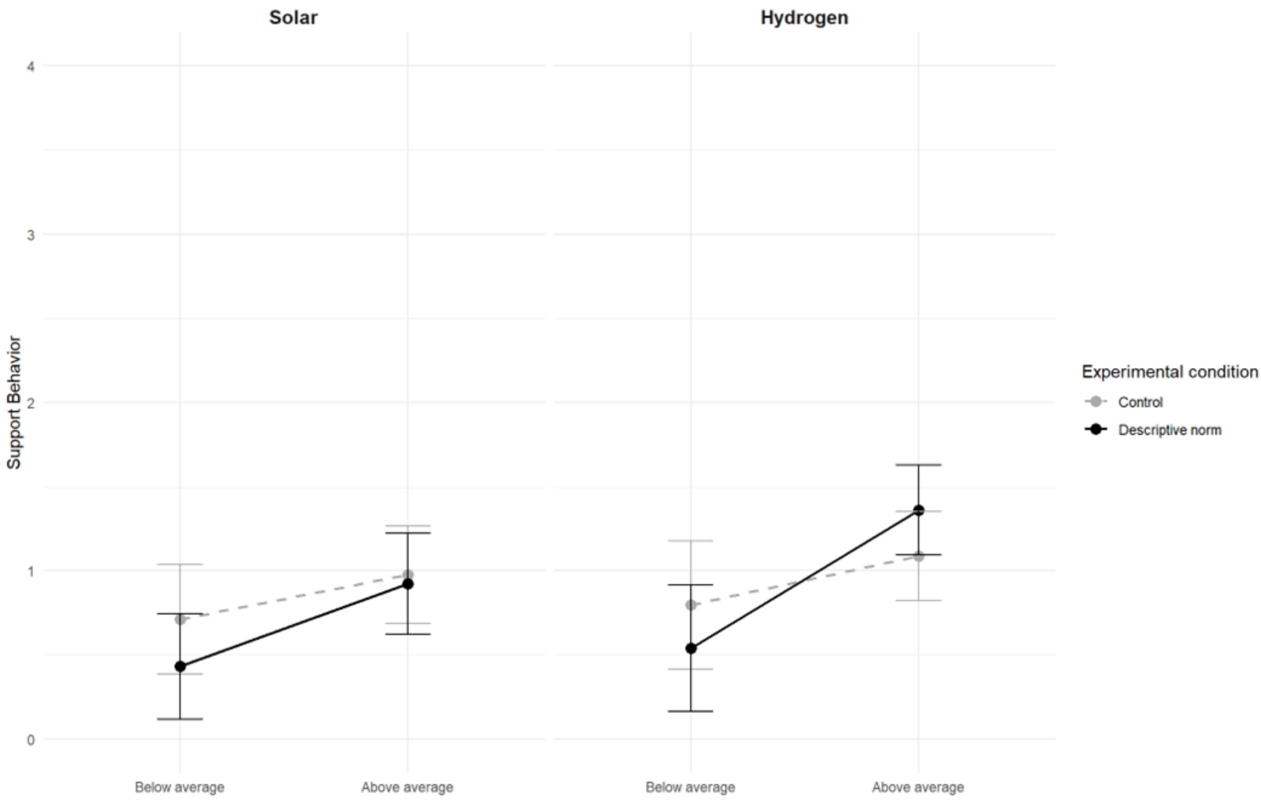
“Experimental condition” ($F_{(1, 592)}$ = .83, p = .301, ω^2 = .001), and “Technology” X “Baseline Support Intention” average ($F_{(1, 592)}$ = .61, p = .392, ω^2 = .001) two-way interactions, and the “Baseline Support Intention” average X “Technology” X “Experimental condition” three-way interaction ($F_{(1, 592)}$ = .42, p = .441, ω^2 = .001) were not significant. Testing the hypothesized differences in participants below the average (H5; descriptive norm > control), no significant effects were found for solar (*MD* = -.28, *SE* = .23, *95% CI* [-.71, .09]) and hydrogen (*MD* = -.26, *SE* = .27, *95% CI* [-.74, .26]) energies, thus leading to a rejection of H5.

Testing the hypothesized differences in participants above the average (H6; descriptive norm < control), no significant effects were found for solar (*MD* = -.05, *SE* = .21, *95% CI* [-.46, .34]) and hydrogen (*MD* = .27, *SE* = .19, *95% CI* [-.16, .67]) energies, thus leading to a rejection of H6.

Moreover, pairwise comparisons highlighted two non-hypothesized significant effects. Considering solar energy, participants in the descriptive norm condition with above-average scores showed a significant difference compared to those with below-average scores (*MD* = .49, *SE* = .22, *95% CI* [.12, .88]). Considering hydrogen energy, participants in the descriptive norm condition with above-average scores showed a significant difference from those with below-average scores (*MD* = .82, *SE* = .24, *95% CI* [.38, 1.24]). These results are shown below in Figure 18.

No differences are reported on control groups for both solar and hydrogen energies.

Figure 18 - *Support Behavior Estimated Marginal Means*



4.3.3.2.3 Indirect effects of the descriptive norm on support behavior

Regarding H7, to test the mediating effect of "Negative Affect" in the relationship between descriptive norm and "Support Behavior", a mediation analysis was conducted among participants below the "Baseline Support Intention" pilot average, investigating the moderation of the dichotomous variable "Technology" across all effects to explore potential differences between the two technologies. The interactions did not reveal significant effects. Specifically, "Technology" did not significantly impact the effect of the descriptive norm on "Negative Affect" (*B* = .10; *SE* = .09; *p* = .280; *95% CI* [-.08, .29]) nor on "Support Behavior" (*B* = -.02; *SE* = .32; *p* = .958; *95% CI* [-.65, .62]). Furthermore, "Technology" did not affect the relationship between "Negative Affect" and "Support Behavior" (*B* = -.75; *SE* = .54; *p* = .171; *95% CI* [-1.81, .32]). Examining conditional effects for each energy technology, for solar energy, descriptive norm did not report a direct effect on "Negative Affect" (*B* = -.10; *SE* = .07; *p* = .153; *95% CI* [-.24, .04]) and "Support Behavior" (*B* = -.24; *SE* = .21; *p* = .253; *95% CI* [-.65, .17]). Additionally, "Negative Affect" was not correlated with "Support Behavior" (*B* = .45; SE = .25; *p* = .080; *95% CI* [-.05, .95]). Lastly, the indirect effect of the descriptive norm on "Support Behavior," mediated by "Negative Affect", was not significant (*B* = -.04; *SE* = .05; *95% CI* [-.17, .02]), thus rejecting H7. Similarly, for hydrogen energy, the descriptive norm did not report a direct effect on "Negative Affect" (*B* = .003; *SE* = .05; *p* = .949; *95% CI* [-.10, .11]) and "Support Behavior" (*B* = -.25; *SE* = .25; *p* = .309; *95% CI* [-.75, .24]). Additionally, "Negative Affect" was not correlated with "Support Behavior" (*B* = -.30; *SE* = .49; *p* = .541; *95% CI* [1.26, .67]). Lastly, the indirect effect of the descriptive norm on "Support Behavior" - mediated by "Negative Affect" - was not significant (*B* = -.001; *SE* = .03; *95% CI* [-.03, .07]), also rejecting H7, as shown in Figure 3C in Appendix C.

Given that the 2x2x2 ANOVA revealed a direct effect of descriptive norm on "Negative Affect" among participants above average regarding solar energy, a non-hypothesized mediation effect of "Negative Affect" between descriptive norm and "Support Behavior" was also tested in this group. The moderation of the dichotomous variable "Technology" was investigated across all effects to explore potential differences between the two technologies. "Technology" significantly impacted the effect of the descriptive norm on "Negative Affect" (*B* = -.21; *SE* = .10; *p* = .039; *95% CI* [-.40, -.01]), reporting a significant effect of descriptive norm only regarding solar energy. On the other hand, "Technology" did not affect the relationship between descriptive norm and "Support Behavior" (*B* = .34; *SE* = .31; *p* = .279; *95% CI* [-.27, .94]), nor the relationship between "Negative Affect" and "Support Behavior" (*B* = .002; *SE* = .33; *p* = .996; *95% CI* [-.64, .64]). When examining the conditional effects for each energy technology, for solar energy, descriptive norm reported a positive direct effect on "Negative Affect" (*B* = .22; *SE* = .07; *p* = .003; *95% CI* [.08, .37]), while did not emerge a direct effect on “Support Behavior” (*B* = -.07; *SE* = .21; *p* = .761; *95% CI* [-.49, .36]). Additionally, “Negative Affect” was not correlated with “Support Behavior” (*B* = .05; *SE* = .23; *p* = .812; *95% CI* [-.39, .50]). Lastly, the indirect effect of the descriptive norm on “Support Behavior,” mediated by “Negative Affect”, was not significant (*B* = .01; *SE* = .06; *95% CI* [-.10, .14]). Considering hydrogen energy, the descriptive norm did not report a direct effect on “Negative Affect” (*B* = .02; *SE* = .07; *p* = .813; *95% CI* [-.12, .15]) and “Support Behavior” (*B* = .27; *SE* = .22; *p* = .212; *95% CI* [-.16, .70]). Additionally, “Negative Affect” was not correlated with “Support Behavior” (*B* = .06; *SE* = .23; *p* = .809; *95% CI* [-.39, .50]). Lastly, the indirect effect of the descriptive norm on “Support Behavior” - mediated by “Negative Affect” - was not significant (*B* = .001; *SE* = .02; *95% CI* [-.04, .03]). These results are shown in Figure 4C in Appendix C.

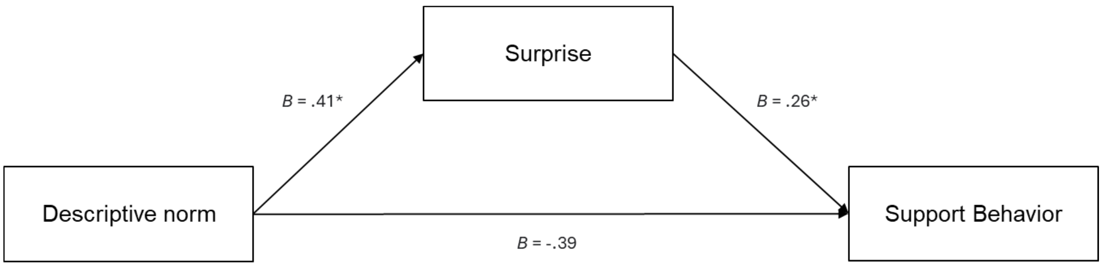
Regarding H8, to test the mediating effect of “Positive Affect” in the relationship between descriptive norm and “Support Behavior”, a mediation analysis was conducted among participants above the “Baseline Support Intention” pilot average, investigating the moderation of the dichotomous variable “Technology” across all effects to explore potential differences between the two technologies. The interactions did not reveal significant effects. Specifically, “Technology” did not significantly impact the effect of the descriptive norm on “Positive Affect” (*B* = .003; *SE* = .20; *p* = .987; *95% CI* [-.38, .39]) nor on “Support Behavior” (*B* = .32; *SE* = .30; *p* = .289; *95% CI* [-.27, .92]). Furthermore, “Technology” did not affect the relationship between “Positive Affect” and “Support Behavior” (*B* = -.05; *SE* = .16; *p* = .775; *95% CI* [-.36, .27]). When examining the conditional effects for each energy technology, for solar energy, descriptive norm did not report a direct effect on “Positive Affect” (*B* = -.06; *SE* = .15; *p* = .702; *95% CI* [-.36, .25]) and “Support Behavior” (*B* = -.04; *SE* = .21; *p* = .842; *95% CI* [-.45, .36]). Additionally, “Positive Affect” was not correlated with “Support Behavior” (*B* = .20; *SE* = .11; p = .056; *95% CI* [-.01, .41]). Lastly, the indirect effect of the descriptive norm on “Support Behavior” - mediated by “Positive Affect” - was not significant (*B* = -.01; *SE* = .04; *95% CI* [-.09, .05]), thus rejecting H8. Similarly, for hydrogen energy, the descriptive norm did not report a direct effect on “Positive Affect” (*B* = -.06; *SE* = .13; *p* = .659; *95% CI* [-.30, .19]) and “Support Behavior” (*B* = .28; *SE* = .22; *p* = .195; *95% CI* [-.14, .70]). Additionally, “Positive Affect” was not correlated with “Support Behavior” (*B* = .16; *SE* = .12; p = .197; *95% CI* [-.09, .39]), and consequently, the indirect effect of descriptive norm on “Support Behavior” - mediated by “Positive Affect” - was not significant (*B* = -.01; *SE* = .03; *95% CI* [-.05, .02]), rejecting H8 (Figure 5C in Appendix C).

Regarding H9, to test the mediating effect of “Surprise” in the relationship between descriptive norm and “Support Behavior”, a mediation analysis was conducted among participants below the “Baseline Support Intention” pilot average, investigating the moderation of the dichotomous variable “Technology” across all effects to explore potential differences between the two technologies. The interactions did not reveal significant effects. Specifically, “Technology” did not significantly impact the effect of the descriptive norm on “Surprise” (*B* = -.04; *SE* = .22; *p* = .872; *95% CI* [-.46, .39]) nor on “Support Behavior” (*B* = -.08; *SE* = .33; *p* = .811; *95% CI* [-.72, .56]). Furthermore, “Technology” did not affect the relationship between “Surprise” and “Support Behavior” (*B* = .30; *SE* = .22; *p* = .167; *95% CI* [-.13, .73]).

Examining conditional effects for each energy technology, for solar energy, descriptive norm showed a direct and positive effect on “Surprise” (*B* = .41; *SE* = .16; *p* = .011; *95% CI* [.10, .73]), but no direct effect on “Support Behavior” (*B* = -.39; *SE* = .21; p = .066; *95% CI* [-.80, .03]). Additionally, “Surprise” was positively correlated with “Support Behavior” (*B* = .26; *SE* = .11; *p* = .021; *95% CI* [.04, .47]). Lastly, the indirect effect of the descriptive norm on “Support Behavior” - mediated by “Surprise” - was positive and significant (*B* = .11; *SE* = .06; *95% CI* [.001, .25]), supporting H9. Similarly, for hydrogen energy, the descriptive norm showed a direct and positive effect on “Surprise” (*B* = .38; *SE* = .13; *p* = .005; *95% CI* [.12, .63]), but no direct effect on “Support Behavior” (*B* = -.45; *SE* = .25; *p* = .065; *95% CI* [-.96, .03]). Additionally, “Surprise” was positively correlated with “Support Behavior” (*B* = .56; *SE* = .19; *p* = .004; *95% CI* [.19, .93]), and the indirect effect of the descriptive norm on “Support Behavior” - mediated by “Surprise” - was positive and significant (*B* = .21; *SE* = .12; *95% CI* [.01, .49]), thereby supporting H9. These results are shown below in Figure 19.

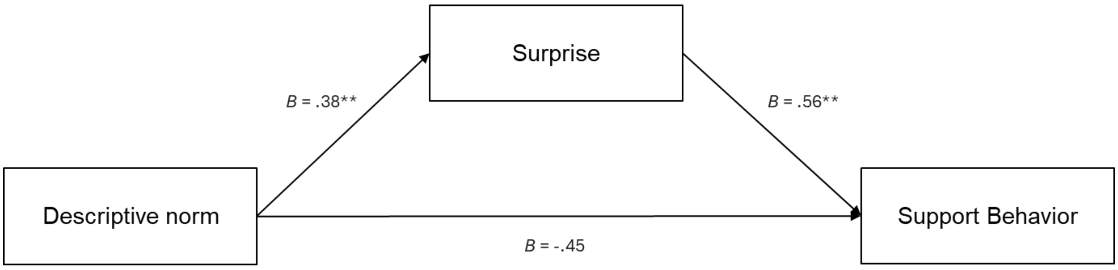
Figure 19 - *Surprise mediation below average (Conditional effects)*

SOLAR



Note: *Dependent variable: Support Behavior; R = .23;* R^2 *= .05 (*$F_{(2,135)}$ *= 3.67, p = .028); Indirect effect: B = .11, BootSE = .06, BootLLCI = .001, BootULCI = .25.*

HYDROGEN



Note: *Dependent variable: Support Behavior; R = .31;* R^2 *= .10 (*$F_{(2,96)}$ *= 5.04, p = .008); Indirect effect: B = .21, BootSE = .12, BootLLCI = .01, BootULCI = .49.*

Given that the 2x2x2 ANOVA revealed a direct effect of the descriptive norm on “Surprise” also among participants above the “Baseline Support Intention” pilot average for both solar and hydrogen energies, a non-hypothesized moderated (on all effects by “Technology”) mediation of “Surprise” in the relationship between descriptive norm and “Support Behavior” was also tested in this group. The interactions did not reveal significant effects. Specifically, “Technology” did not significantly impact the effect of the descriptive norm on “Surprise” ($B = -.07$; $SE = .25$; $p = .773$; *95% CI* [-.55, .41]) or on “Support Behavior” ($B = .34$; $SE = .31$; $p = .282$; *95% CI* [-.28, .95]). Additionally, “Technology” did not influence the relationship between “Surprise” and “Support Behavior” ($B = -.01$; $SE = .13$; $p = .942$; *95% CI* [-.27, .25]).

Examining the conditional effects for each energy technology, for solar energy, the descriptive norm had a direct and positive effect on “Surprise” ($B = .57$; $SE = .19$; $p = .003$; *95% CI* [.20, .94]), but no direct effect on “Support Behavior” (B = -.11; SE = .21; p = .613; *95% CI* [-.53, .31]). Additionally, “Surprise” did not correlate with “Support Behavior” ($B = .10$; $SE = .09$; $p = .274$; *95% CI* [-.08, .27]). Therefore, the indirect effect of the descriptive norm on “Support Behavior” - mediated by “Surprise” - was non-significant ($B = .05$; $SE = .06$; *95% CI* [-.05, .18]). Similarly, for hydrogen energy, the descriptive norm had a direct and positive effect on “Surprise” ($B = .50$; $SE = .16$; $p = .002$; *95% CI* [.18, .82]), but no direct effect on “Support Behavior” ($B = .23$; $SE = .22$; $p = .303$; *95% CI* [-.21, .66]). Additionally, “Surprise” did not correlate with “Support Behavior” ($B = .09$; $SE = .09$; $p = .358$; *95% CI* [-.10, .27]). Therefore, the indirect effect of the descriptive norm on “Support Behavior” - mediated by “Surprise” - was non-significant ($B = .04$; $SE = .05$; *95% CI* [-.05, .15]) (see Figure 6C in Appendix C).

Regarding H10, to test the mediating effect of “Contentment” in the relationship between descriptive norm and “Support Behavior”, a mediation analysis was conducted among participants above the “Baseline Support Intention” pilot average, investigating the moderation of the dichotomous variable "Technology" across all effects to explore potential differences between the two technologies. The interactions did not reveal significant effects. Specifically, "Technology" did not significantly impact the effect of the descriptive norm on "Contentment" (*B* = .002; *SE* = .25; *p* = .993; *95% CI* [-.49, .49]) nor on "Support Behavior" (*B* = .31; *SE* = .30; *p* = .301; *95% CI* [-.28, .91]). Furthermore, "Technology" did not affect the relationship between "Contentment" and "Support Behavior" (*B* = -.08; *SE* = .13; *p* = .545; *95% CI* [-.33, .18]). When examining the conditional effects for each energy technology, for solar energy, descriptive norm did not report a direct effect on "Contentment" (*B* = -.13; *SE* = .19; *p* = .500; *95% CI* [-.49, .24]) and "Support Behavior" (*B* = -.03; *SE* = .21; *p* = .877; *95% CI* [-.44, .37]). Additionally, "Contentment" was not correlated with "Support Behavior" (*B* = .17; *SE* = .09; *p* = .056; *95% CI* [-.005, .34]). Lastly, the indirect effect of the descriptive norm on "Support Behavior" - mediated by "Contentment" - was not significant (*B* = -.02; *SE* = .04; *95% CI* [-.11, .04]), thereby rejecting H10. Similarly, for hydrogen energy, the descriptive norm did not report a direct effect on "Contentment" (*B* = -.12; *SE* = .17; *p* = .458; *95% CI* [-.45, .20]) and "Support Behavior" (*B* = .28; *SE* = .22; *p* = .192; *95% CI* [-.14, .71]). Additionally, "Contentment" was not correlated with "Support Behavior" (*B* = .09; *SE* = .09; *p* = .330; *95% CI* [-.09, .27]), and consequently, the indirect effect of descriptive norm on "Support Behavior" - mediated by "Contentment" - was not significant (*B* = -.01; *SE* = .03; *95% CI* [-.08, .02]), thus rejecting H10 (see Figure 7C in Appendix C).

4.3.4 Discussion

Study 3b revealed results that contrast previous studies (Studies 1 and 2). Specifically, unlike the findings of the earlier studies and previous research in environmental psychology (Chen et al., 2016; Vesely et al., 2022), no direct impact of descriptive norms on SETs support was observed. However, similar findings have emerged in the literature, highlighting that the effect of descriptive norms on intentions and behaviors is often mediated by third variables (e.g., personal norms; Fornara et al., 2016; Wang & Zhang, 2020).

Moreover, the literature shows that the effect of norms on behaviors is strongly influenced by the centrality perception of the normative group and how much the individual identifies with it (see Terry & Hogg, 1996). Referring to fellow residents as a normative group might have been too weak as a reference for some participants - particularly since the Californian identification was not controlled - partially explaining the lack of a direct effect of descriptive norm on behavior.

This study, then, focusing for the first time on the impact of descriptive norms on emotional responses (see Packard & Schultz, 2023), revealed significant results that could paving the way for future research on the relationship between social comparison and emotions in environmental decision-making contexts, particularly regarding energy-related behaviors.

Interestingly, social comparison did not impact broad emotional factors, as indicated by the minimal effect on positive and negative affect (as measured by Watson et al., 1988). Instead, it appears to influence specific emotions, as shown in previous studies examining personal norms (e.g., Fessler, 2007) and injunctive social norms (e.g., Suhay, 2015) concerning emotions like shame and pride.

As hypothesized by Packard and Schultz (2023), descriptive norms seem to influence specific neutral valence emotions (particularly surprise) similarly to how personal and injunctive norms influence positive and negative valence emotions (i.e., pride, shame, guilt; Diel & Friese, 2024; Diel, Grelle, & Hofmann, 2021). In contrast, social comparison did not affect low-arousal emotions such as contentment. This may be due to the structural difference between these emotions, namely surprise is neutral in valence but high in arousal, while contentment is positive in valence but low in arousal (see Russell, 1980; Russell, 1991). This interpretation could suggest that descriptive norms may thus influence neutral-valence high-arousal emotions but not low-arousal emotions.

Another explanation for the observed effect of descriptive norm on “Surprise” but not “Contentment” may lie in Packard and Schultz’s (2023) conceptualization of emotional responses to norm deviance and conformity. In the present study, we focused solely on deviance - considered pro-environmental and anti-environmental - rather than distinguishing between deviance and conformity. This may also explain the not hypothesized effect of descriptive norms on “Surprise” among pro-environmental deviants, as also confirmed by Noordewier and Gocłowska (2024) wich suggest that exceeded and disconfirmed expectancies could generate surprise.

In line with Schultz et al. (2007), then, this feeling of surprise would increase PEBs only among anti-environmental deviants, while pro-environmental deviants would show behavioral deactivation (see Lazarus, 1991). This is supported by the mediation analyses showing the effect of “Surprise” on both pro- and anti-environmental deviants (see paragraph 4.3.3.2).

The study also reveals a non-hypothesized effect of descriptive norm among “above average” participants on “Negative Affect” (specifically regarding solar energy). This effect may be driven by negative emotions, such as feelings of moral outrage (e.g., Thomas & McGarty, 2009), which have been linked in the literature to perceiving others as failing to fulfill socially beneficial actions. Knowing that others are behaving less pro-environmentally than oneself may evoke negative emotional reactions due to concerns for the environment and the climate crisis. Additionally, through group identification effects opposite from those mentioned above, highly identified individuals may experience negative emotions as a reflection of internalized group-based emotions (Kuppens & Yzerbyt, 2012; Van Kleef & Fischer, 2016). Similarly, negative emotions could be tied to concerns about the group’s reputation, which is central to highly identified members (e.g., Allpress et al., 2014).

The findings also revealed that participants who were more willing to support SETs ("above average") experienced stronger positive and negative emotional reactions. In terms of "Positive Affect" and "Contentment", these emotional responses may be related to phenomena such as the warm glow effect (see Andreoni, 1990), where performing PEBs induces positive emotions (Hartmann et al., 2017). Even in the control condition, indeed, the feedback provided to participants might have led them to assess their scores based on an implicit norm, such as the average response scale, leading participants with high scores to perceive their behavior as pro-environmental. Moreover, the absence of a descriptive norm effect on positive emotions in both below- and above-average participants could be attributed to this implicit norm influence. However, due to the different nature of emotional responses like "Negative Affect" and "Surprise", the effect of the "Baseline Support Intention" average on all the emotional responses is more likely tied to a higher level of involvement and commitment to environmental issues among "above average" participants. This deeper engagement could lead them to experience more intense emotions than their "below average" fellow residents (see Conte et al., 2023).

Another interesting finding emerged when comparing the emotional responses to different technologies. Regardless of their "Baseline Support Intention" average or the type of feedback received, participants who answered the questionnaire about solar energy reported more positive emotional responses ("Positive Affect" and "Contentment") than those who answered questions about hydrogen energy, probably due to the greater feasibility and knowledge participants attribute to solar energy. On the other hand, the study confirms the findings from Study 1 (Milani, Dessi, & Bonaiuto, 2024) and Study 2, showing no substantial differences between solar and hydrogen energy acceptance processes.

Lastly, regarding hypotheses 3 and 4, the results offer methodological insights, showing that repeated questioning (on support intention) leads to decreased support intention, regardless of the experimental condition or “Baseline Support Intention” average. Future studies may consider using different measures to assess the same construct to avoid similar effects.

CHAPTER 5

Discussion and implications

5.1 General discussion

In summary, this project aimed to identify what drives people to socially accept and eventually adopt and support mitigation and adaptation SETs. Specifically, by focusing on beliefs about the characteristics of the technology, the adoption context, and the adopters themselves, the project sought to answer two key questions. First, it aimed to identify the main drivers and barriers to the social acceptance of these technologies. Second, it explored whether there are differences in the social acceptance processes of various mitigation technologies and between mitigation and adaptation technologies.

Across the three studies, using various methodological approaches, the main barriers and drivers of SETs were identified. The findings, consistent with the theoretical framework of Bonaiuto et al. (2023, 2024), highlighted that these antecedents primarily fall into three categories of beliefs: technological features, contextual features, and adopter's personal beliefs. The studies underscored the importance of beliefs regarding the relationship between the individual and the technology, and particularly between the individual and the adoption context. Additionally, the research found that the social acceptance processes for different technologies - despite differences in TRLs and individual perceptions - did not vary substantially. This suggests that understanding what drives people to socially accept specific energy technologies may help explain the broader social acceptance of various SETs. Despite structural differences between mitigation and adaptation technologies, as well as the unique challenges hindering their social acceptance (as noted by Corner & Pidgeon, 2010; Sovacool, Baum, & Low, 2022a), the first two studies revealed no significant differences in the social acceptance processes of these technologies. This insight underscores the potential for generalizing findings across various energy technologies.

In detail, Study 1, using a meta-analytic approach, first and foremost highlighted the centrality of acceptability as a key predictor of acceptance. Similarly, variables related to the perception of adoption consequences (both cognitive and affective) emerged to be the main predictors of acceptability. Conversely, acceptance turns out to be more predicted by variables related to the context and its adopters' perception. This is crucial to understand how acceptability, having a cognitive and affective nature (see Brunson & Shindler, 2004), seems to reflect beliefs and feelings toward SETs. What then seems to turn this acceptability into acceptance are fundamentally contextual factors. A positive attitude toward SETs (acceptability) would thus be the first and most important step toward acceptance and adoption, but this will probably have to be driven by the pull of the external context, as also suggested by Kowalska-Pyzalska (2018) and Bonaiuto et al. (2024). For transforming acceptability into acceptance, variables related to the actual use of the technology, also seem crucial, highlighting that for acceptability to be transformed into acceptance, it is necessary to perceive the technology as easy to use and reliable (Masukujjaman et al., 2021), as previously proposed by Davis and colleagues (Davis, 1989; Davis et al., 1989), and deeply investigated by Marangunić and Granić (2015). This is consistent with previous studies (e.g., Steg & Vlek, 2009) and classical theories (e.g., TPB; Ajzen, 1991), which emphasize the role of contextual factors in transforming attitudes into intentions. The intention, being inherently behavior-oriented, is not always driven solely by individual preferences and perceptions. Instead, it is often the interaction of contextual factors with individual preferences and perceptions that impact behavior (Ertz et al., 2016). These findings highlight the importance of considering the broader situational context when studying how attitudes influence pro-environmental actions.

Study 2, through a cross-sectional and correlational approach aimed at empirically testing the theoretical model proposed by Bonaiuto and colleagues (2024), situates itself within the broader context of research on normative influence (Cialdini et al., 1990, 1991; Schwartz, 1968, 1977). It confirms the crucial role of personal and social norms in influencing different categories of SETs. These findings align with Steg and Vlek (2009), emphasizing the importance of moral and social norms in promoting PEBs. The study reinforces the need for ongoing research to understand what drives people to follow or disregard such norms and in which specific contexts these norms are more effective and, therefore, more encouraging. Furthermore, the study highlights the affective component's centrality - as shown in Study 1 (Milani, Dessi, & Bonaiuto, 2024) - in promoting the acceptability and acceptance of these technologies. Study 2 also echoes the previous study in underscoring the importance of acceptability in catalyzing the effects of specific beliefs on acceptance. This is especially evident concerning the results on the effects of the affective response to the risks and benefits of the technology in predicting technology acceptance. When considering the intention to use and spend money on technology as acceptance, indeed, the emotional response does not report a direct effect but only a mediated effect (by acceptability). Finally, the study suggests that different facets of social acceptance - the intention to support, willingness to spend money, or directly adopting the technology - are driven by similar processes, with only marginal differences, as noted in Section 2.3.1 of Study 1.

Finally, through the graphical approach (i.e., PNA), Study 2 reveals that mitigation and adaptation SETs are perceived differently, which can lead to divergent acceptance processes. The study emphasizes the importance of perceiving adaptation technologies as "necessary" for their support and use. It also shows that less familiar technologies tend to have simpler and smaller attitude networks, confirming the assumptions of the CAN models. Specifically, the study supports that "*individual with much knowledge about an attitude object will also have* *many different evaluative reactions*" (Dalege et al., 2016, p. 33). Increasing public familiarity with certain technologies may, therefore, enrich the complexity of attitudes toward them, potentially fostering broader acceptance.

Study 3, using an experimental approach to further investigate the specific relationships identified in previous studies, focuses on the impact of descriptive social norms on PEBs (particularly energy-related PEBs) and the reinforcing role of emotions elicited by social comparison in mediating the effects of these norms (see paragraph 1.3). The study examines two mitigation SETs (solar and hydrogen energies), finding no direct effect of descriptive social norm on supportive behaviors toward SETs. However, the study highlights that this norm significantly impacts feelings of surprise (as hypothesized by Packard & Schultz, 2023), showing that deviating from the norm - whether in a pro- or anti-environmental direction - elicits feelings of surprise. Interestingly, the research reveals that experiencing surprise increases the likelihood of engaging in energy-related PEBs (technology support), but only for anti-environmental deviants. For pro-environmental deviants, feelings of surprise do not seem to influence their subsequent behaviors. These findings, consistent with classic studies on normative influence (e.g., Schultz et al., 2007), introduce new avenues for research into the relationship between descriptive norms and emotions in driving energy-related PEBs and other PEBs, as discussed in paragraph 4.3.4. This offers fresh insights into how emotional responses, particularly surprise, may shape environmental behaviors differently depending on the individual's normative alignment.

5.2 Implications

This project presents numerous theoretical and practical implications regarding the social acceptance of SETs and their subsequent adoption. Theoretically, it aims to enrich the current State of Art by advancing new theoretical proposals and analyzing various technologies. The goal is to open up new theoretical and practical horizons, offering insights that could guide future research and applications in SETs acceptance. Specifically, Study 1 presents itself as the first meta-analysis in the literature to encompass a wide range of energy technologies. Despite some limitations (see paragraph 5.3), the study seeks to provide a comprehensive overview of the literature on the social acceptance of energy technologies. Building on the framework proposed by Bonaiuto et al. (2023, 2024), the study supports the systematic theorization and classification of the social acceptance process by analyzing different belief clusters and distinguishing between acceptability and acceptance, highlighting their nuances and differences. The results identify the main drivers of both acceptability and acceptance and the types of beliefs they belong to and emphasize the need to distinguish between the two concepts due to the different social-psychological processes that promote them. The study underlines the crucial theoretical importance of the affective component, which strongly influences social acceptance but has been marginally explored (see Cousse, 2021; Cousse et al., 2020; Cousse et al., 2021). Additionally, it highlights the central role of contextual factors - as discussed in paragraph 5.1 - in facilitating the transition from acceptability to acceptance and, ultimately, to the adoption and support of these technologies. Study 2 empirically validates the model Bonaiuto and colleagues (2024) proposed and supports the findings from Study 1 (Milani, Dessi, & Bonaiuto, 2024). Theoretically, it also highlights the potential of using graphical methods in environmental psychology (as noted by Bhushan et al., 2019), particularly in social acceptance (see Scovell et al., 2024). Along with the previous study, this research offers new evidence - previously scarce - regarding the similarities and differences that drive the social acceptance of mitigation and adaptation SETs.

Finally, the Thesis, focusing on the relationship between the individual and the context in the process of social acceptance, provides first empirical evidence of the effect of descriptive norms on individuals' emotional sphere (Study 3), comparing different mitigation SETs. The study identifies a specific effect of descriptive norm on the emotional experience of surprise and highlights the “selective power” of surprise in promoting PEBs. This finding contributes to the still unclear literature on descriptive norms and emotional reactions. This key result from Study 3 - partially aligned and partially opposed to classic surprise theories like the cognitive-evolutionary model of surprise (Meyer et al., 1997) and the inference theory of surprise (see Reisenzein et al., 2019) - suggests that surprising events trigger a mental process involving the recognition of deviations from expected norms, which reallocates cognitive resources to evaluate the event and, if necessary, revise existing schemas. Thus, the emotional response of surprise due to social comparison seems to trigger similar processes to those called by Vining & Merrick (2012) “environmental epiphanies”, in which unexpected environmental experiences provoke specific emotional reactions (such as surprise), subsequently influencing the human-nature interaction.

While the cognitive-evolutionary model of surprise (Meyer et al., 1997) and the inference theory of surprise (Reisenzein et al., 2019) propose that the intensity of surprise correlates with the unexpectedness of the event and thus motivates further investigation and action (Reisenzein, 2000), findings from Study 3 only partially support this, especially in comparisons between descriptive norms and the control group. On the other hand, although above-average participants experienced more surprise, only below-average participants changed their behavior. These results provide important theoretical insights, suggesting that classical surprise theories may interact with social comparison and normative influence theories (Cialdini et al., 1990, 1991), indicating that not only the intensity of surprise but also its cause influences subsequent behavior. This reflects the ongoing ambiguity in the literature regarding the valence of surprise (see Neta & Kim, 2023; Ortony, 2022; Ortony & Russell, 2024). Finally, findings related to negative affect offer other initial insights for future research on how descriptive norms impact the emotional sphere and whether these emotional responses can influence subsequent behaviors.

From a practical standpoint, this Thesis offers several actionable insights and implications for promoting the social acceptance of SETs. Specifically, the findings from Study 1 suggest that to increase future adoption of SETs, it is crucial not only to promote their acceptability and enhance their perception and reputation but also to foster a favorable perception of the adoption context and improve the usability of the technology. These strategies will be pivotal in encouraging widespread acceptance and adoption of SETs. The findings also indicate that communication efforts should emphasize the emotional appeal and tangible benefits of adopting these technologies, such as reducing carbon footprints, improving public health, and generating economic savings. Highlighting fairness and transparency in the development and deployment processes can foster public trust, especially when local communities are involved in decision-making and the distribution of benefits is equitable. Policy-wise, government incentives like subsidies and tax deductions play a crucial role in encouraging adoption, making these technologies more accessible. A clear regulatory framework that supports their deployment can also increase perceived reliability and ease of use, driving further public acceptance. Additionally, cultural and regional differences in acceptance must be acknowledged, as factors like perceived control and subjective knowledge exert varying influences across Eastern and Western contexts. Therefore, awareness campaigns should be tailored to align with the cultural norms of specific regions. Targeting younger, tech-savvy demographics is also essential, given the significance of “consumer innovativeness” and “perceived behavioral control” in driving acceptance; using digital platforms to communicate the benefits and usability of these technologies could be particularly effective. Lastly, since social norms significantly influence acceptance, cultivating a community culture that supports sustainable practices is important. This can involve endorsements from trusted figures or showcasing local success stories in renewable energy adoption, thereby embedding pro-environmental behaviors within social habits and encouraging widespread adoption.

The findings from Study 2 reinforce the significant role of normative influence, as both personal and social norms directly impact the acceptability and acceptance of mitigation and adaptation SETs. This suggests that public campaigns should not only target individual attitudes but also emphasize social expectations and moral obligations related to supporting and adopting SETs, for example, by promoting an identity connection between citizens and the technologies (Kalkbrenner & Roosen, 2016; Seyfang & Haxeltine, 2012). Emotional responses to perceived risks and benefits are also crucial in shaping acceptability, indicating that messaging strategies should evoke positive emotions by emphasizing the societal and personal benefits of SETs, such as reducing climate change impacts or contributing to energy independence. Furthermore, the study demonstrates that enhancing the perception of SETs as necessary is particularly important for adaptation technologies, which may be seen as less urgent by the public. Therefore, communication strategies should stress the necessity and potential future benefits of adaptation technologies to boost their acceptance. For mitigation technologies, which are more complexly associated with various attributes of acceptability, efforts should focus on addressing multiple dimensions, such as the safety, effectiveness, and attractiveness of these technologies. The findings also underline the need to improve overall public perceptions of SETs, as levels of acceptability remain relatively low. Efforts should target specific characteristics of the technologies that influence acceptability and acceptance, such as promoting their necessity, safety, and economic benefits. Additionally, the invariance found between the acceptance processes for mitigation and adaptation technologies suggests that strategies aiming at fostering SETs acceptance can be grounded in shared principles, focusing on key factors like normative influence, positive emotional appeal, and perceived necessity. These approaches should be integrated into public policies, educational programs, and promotional campaigns to enhance social readiness for adopting sustainable energy technologies.

The findings from Study 3 offer valuable practical implications, especially when considering the implementation of normative communication strategies aimed at persuading the general public. Empirical evidence from the literature (e.g., Schultz et al., 2007) suggests that it is crucial to understand the audience before delivering persuasive messages that leverage normative influence. This is particularly important because normative messages have varying effects on pro- and anti-environmental deviants and conformists. Additionally, descriptive and injunctive norms, as well as their interaction, impact these groups differently. To optimize the effectiveness of such interventions, the decision-making process should align with models like the "*social norm intervention decision tree*" proposed by Farrow et al. (2017).

Furthermore, the study provides important insights into how norms influence emotional responses and how these emotions, in turn, affect behavior. This highlights that experiencing specific emotions can lead to conditional effects depending on the audience, reinforcing the importance of tailoring communication strategies based on these insights.

5.3 Limitations

This project and the individual studies within it present several limitations. Specifically, while the project aimed to offer broad generalizability by investigating a wide range of energy technologies, it did not explore the social acceptance of SETs in populations undergoing specific and active energy transitions or in targeted demographics (e.g., homeowners and farmers). This limited the ability to conduct an in-depth analysis of the everyday dynamics that drive the adoption and support of these technologies. Similarly, by focusing on broad categories of technologies or examining multiple technologies together, the Thesis could not delve into how the specific characteristics of single technologies or real-world case studies might affect their social acceptance.

Considering Study 1, a first limit is that, despite these meta-analyses aim to be inclusive of every relevant factor in the energy technology acceptance literature, some factors were not included in the analyses, although they are able to influence the acceptability and acceptance of different SETs, such as values (e.g., de Groot et al., 2013; Perlaviciute & Steg, 2015). Although values were included in the search string, they did not indeed lead to enough studies, as in many studies, value related variables were more reflective of other psychological constructs (such as personal norm).

A second limit is reflected by the fact that although the research considers a large number of studies analyzing different SETs, many technologies are under-represented. Most studies examine mitigation technologies, particularly solar energy (see Figure 20 and 21). This overestimation of some technologies (e.g., renewable mitigation energy technologies) at the expense of others (e.g., geoengineering) leads to reduced generalizability of the Study 1 results, and a call for higher technological variety in future research.

Figure 20 - *Frequencies of Acceptability determinants: Variable x Technology*

	Solar	Wind	Biofuels	Tidal	Hydroelectric	Hydrogen	CCS	Geoengineering	Multiple	Total
Perceived benefits	2	9	4	0	1	1	8	1	4	30
Positive emotional response	0	0	1	2	0	1	2	1	2	9
Fairness	0	4	1	0	0	0	2	0	2	9
Trust in decision makers	2	4	4	0	1	1	5	2	3	22
Perception of human impact on climate change	0	1	0	0	0	0	3	1	2	7
Climate change concern	1	5	1	0	0	0	7	0	0	14
Place attachment	0	3	2	2	0	0	1	0	0	8
Subjective knowledge	2	0	1	0	0	0	5	1	2	11
Income	4	4	1	0	0	0	5	0	3	17
Education	4	1	2	0	0	0	7	0	8	22
Woman	6	4	2	0	0	0	6	0	9	27
Conservative	5	2	1	0	0	0	4	0	3	15
Negative emotional response	0	0	0	2	0	0	1	1	1	5

Figure 21 - *Frequencies of Acceptance determinants: Variable x Technology*

	Solar	Wind	Biofuels	CCS	Geoengineering	Multiple	Total
Attitude	10	0	7	2	1	10	30
Government initiatives	5	0	0	1	0	1	7
Trust in decision makers	3	0	2	2	1	1	9
Perceived benefits	15	2	2	1	0	9	29
Perceived ease of use	4	0	0	0	0	4	8
Social norms	16	0	5	1	1	13	36
Consumer innovativeness	6	0	0	0	0	1	7
Perceived behavioral control	9	0	5	0	0	11	25
Climate change concern	8	0	0	1	1	10	20
Personal norm	2	0	2	0	0	4	8
Perceived technology reliability	3	0	1	0	0	2	6
Ecological lifestyle	4	0	0	1	1	0	6
Subjective knowledge	11	0	3	1	1	9	25
Woman	3	0	5	1	0	0	9
Education	8	0	3	1	0	1	13
Income	4	1	3	0	0	1	9
Perceived cost	12	0	1	0	0	9	22

A third issue of Study 1 is that the analyses report high heterogeneity among the studies. As previously mentioned (see paragraph 2.3.1), although several moderators have been hypothesized to explain such limit, testing moderation analyses has not always been possible.

Finally, another limitation of Study 1 is related to the uneven distribution of studies across continents, with a massive prevalence of studies from the North American, European, and Asian continents. In contrast, studies from the Central and South American, African, and Oceanic continents turn out to be underrepresented, leading to reduced generalizability.

Regarding Study 2, a key limitation lies in the fact that, although people cannot directly use adaptation technologies, the intention to adopt these technologies (and mitigation technologies, for comparison) was measured by assuming such agentivity. This reduces the applicability of the results, particularly for adaptation technologies, as they are based on intentions for behaviors that are not currently actionable (hypothetical). As a result, the findings may reflect participants' values and attitudes more than their actual behaviors. A second limitation, closely related to the first, is that the study measured intention (acceptance) as a proxy for actual behavior (support or adoption) rather than measuring behavior directly. This limitation was addressed in Study 3, which included a measure of actual behavior.

Considering the limitations of Study 3, the main issue - discussed in paragraph 4.3.4 - is that, although Study 3 primarily references the conceptual framework developed by Packard and Schultz (2023), the study focused solely on deviance (both pro-environmental and anti-environmental) rather than distinguishing between deviance and conformity. While the authors theorized specific emotional responses to both conformity and deviance, these were applied to a context of pro- and anti-environmental deviance, assuming that pro-environmental deviance could be equated with conformity. This likely impacted on the results, as extensively discussed in Chapter 4. A second limitation involves the dependent variables' low mean and median scores, indicating reduced variability across conditions. A third methodological limitation is that the behavior on which normative feedback was given differed from the target behavior measured in the study. This, like the first limitation, may have significantly influenced the findings. Specifically, the support intention scale used to establish normative feedback did not refer to commitment behaviors towards the technology, unlike the behavior used in the experiment. Lastly, an additional limitation is the underrepresentation of below-average groups compared to above-average groups, which resulted in lower statistical power for analyses involving these groups, particularly concerning hydrogen energy. This phenomenon was due to an unexpectedly lower willingness to support the examined SETs among pilot study participants if compared with experiment participants.

Finally, considering an additional limitation of the Thesis as a whole, while it experimentally investigates the role of social (descriptive) norms in influencing the acceptance of SETs, it does not experimentally examine the impact of personal norm and emotional responses on the acceptability and acceptance of these technologies. Future studies could address this gap by experimentally investigating these relationships to test the hypothesized causal links.

5.4 Future directions

Given the abovementioned limitations, numerous opportunities exist to improve this research and address unanswered questions. Additionally, this Thesis's theoretical and applied contributions have revealed new research avenues in the social acceptance of SETs and emerging questions that warrant further investigation. The project as a whole underscores the need for more focused studies on specific behaviors and technologies that remain underrepresented. The research also highlights the role of specific beliefs, suggesting that future studies should explore in which contexts these beliefs more effectively promote SETs acceptance. Finally, the thesis emphasizes the necessity of studying the social acceptance of adaptation technologies from an SSH perspective, as noted in numerous studies (see paragraph 1.1). The limited research on adaptation energy technologies - particularly the near-absence of studies examining the effects of social norms, personal norms, and emotional reactions - indicates a significant literature gap, likely due to the unique applications and reduced diffusion of these technologies. With substantial experience gained from mitigation energy technologies, SSH scientists are encouraged to act proactively, developing a social-psychological framework to promote the adoption of adaptation technologies as they become mature and essential. As previously discussed, the insights gained from mitigation technologies should be tailored to suit the distinct characteristics of adaptation technologies.

An analysis of the individual studies, particularly their results and limitations, reveals specific future research directions. Study 1 highlights the need for additional meta-analytic research focusing on variables that did not emerge in this study, such as values, to examine their effects on the acceptability and acceptance of SETs. Given the pivotal role of the affective component in influencing the social acceptance of these technologies and the limited body of research on this topic, it would be crucial to explore the types of emotional responses involved, their impact, and their interaction with other variables. The study further underscores the need to investigate the factors that lead from acceptability to acceptance. While this Thesis has examined what promotes both acceptability and acceptance and their relationship, it remains unexplored which factors and beliefs interact with acceptability to foster acceptance. Findings from Study 1 suggest that contextual factors may influence this relationship, a hypothesis that could be pursued in future studies.

Study 2 provides a key avenue for future research, highlighting the importance of perceiving adaptation technologies as necessary to promote their acceptance. Future studies could investigate, both correlationally and experimentally, how the perception of necessity impacts the social acceptance of various technologies. Additionally, given the challenges in measuring behavioral intentions related to real actions for adaptation technologies, future research could focus on measuring non-hypothetical behavioral intentions toward adaptation technologies.

Study 3 offers numerous insights for future research regarding the analysis of social acceptance of SETs and the role of descriptive norms and their interaction with emotional reactions in promoting PEBs. First, future studies should deeply explore the relationship between descriptive norms and surprise and between surprise and PEBs (see paragraph 5.2). Further research could also examine the ability of descriptive norms to influence only certain types of emotions, particularly based on arousal levels, by investigating the effect of social comparison on a wider range of high-arousal, neutral-valence emotions, and low-arousal, negative-valence emotions not covered in Study 3. Additionally, it would be valuable to study why people experience negative emotions when they know others are behaving less pro-environmentally than they are and to test the speculations presented in Study 3 (e.g., regarding outrage). Future research could also investigate why individuals who act more pro-environmentally than others, even without knowledge of the descriptive norm, tend to feel more intense emotional responses (both positive and negative) than others. Finally, future studies could explore the relationship between feasibility, awareness, and emotional responses to descriptive norms, particularly focusing on positive emotional reactions, as observed in Study 3.

CONCLUSION

In a world of constant progress and evolution, shaped by rapid social and environmental changes, adapting to these shifts and managing them to minimize harm to humanity has become essential. Over recent decades, as urbanization has surged globally, human impact on Earth's ecosystems has intensified, driving unprecedented and large-scale changes. Humanity must respond to these challenges, seeking ways to mitigate and adapt to the transformations underway. Amid these changes, technological advancements offer promising solutions, especially SETs that aim to mitigate climate change and support ecosystems and human communities in adapting. From a psychosocial perspective, fostering a society ready to engage with these technologies is as vital as the technologies themselves. Understanding human behavior regarding SETs is crucial, particularly as personal and social factors - which may, in turn, be promoted or discouraged - influence it. Efforts to raise awareness and reduce behavioral barriers (see van Valkengoed et al., 2024) can create a society more prepared for the widespread adoption of these technologies. Following the theoretical framework of Bonaiuto et al. (2023, 2024), this work focuses on individual beliefs about these technologies, their adoption context, and the interaction between people and technology, and people and adoption context. That Thesis sought to provide theoretical-applicative answers to the continuing need to integrate technological development within the social network that must accommodate it, in the fight against climate change. Furthermore, drawing on the Focus Theory of Normative Conduct (Cialdini et al., 1990, 1991) and on its deepening proposed by Schultz and colleagues (Packard & Schultz, 2023; Schultz et al., 2007), this work highlights how social comparison phenomena may help promote support for and adoption of these technologies, suggesting multiple avenues for theoretical and applied intervention.

References

Abrahamse, W., & Steg, L. (2009). How do socio-demographic and psychological factors relate to households' direct and indirect energy use and savings?. *Journal of economic psychology*, *30*(5), 711-720. https://doi.org/10.1016/j.joep.2009.05.006

Abrahamse, W., & Steg, L. (2013). Social influence approaches to encourage resource conservation: A meta-analysis. *Global environmental change*, *23*(6), 1773-1785. https://doi.org/10.1016/j.gloenvcha.2013.07.029

Abrahamse, W., Steg, L., Vlek, C., & Rothengatter, T. (2007). The effect of tailored information, goal setting, and tailored feedback on household energy use, energy-related behaviors, and behavioral antecedents. *Journal of environmental psychology*, *27*(4), 265-276. https://doi.org/10.1016/j.jenvp.2007.08.002

Abrams, D., & Hogg, M. A. (2010). Social identity and self-categorization. In J.F. Dovidio, M. Hewstone, P. Glick, & V.M. Esses (Eds.), *The SAGE handbook of prejudice, stereotyping and discrimination* (pp. 179-193). SAGE Publishing.

Abreu, J., Wingartz, N., & Hardy, N. (2019). New trends in solar: A comparative study assessing the attitudes towards the adoption of rooftop PV. *Energy Policy*, *128*, 347-363. https://doi.org/10.1016/j.enpol.2018.12.038

Ajzen, I. (1991). The Theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*, 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. *Journal of applied social psychology*, *32*(4), 665-683. https://doi.org/10.1111/j.1559-1816.2002.tb00236.x

Al-Ghussain, L. (2019). Global warming: review on driving forces and mitigation. *Environmental Progress & Sustainable Energy, 38*(1), 13-21. https://doi.org/10.1002/ep.13041

Aldy, J. E., Kotchen, M. J., & Leiserowitz, A. A. (2012). Willingness to pay and political support for a US national clean energy standard. *Nature Climate Change, 2*(8), 596-599. https://doi.org/10.1038/nclimate1527

Allcott, H. (2011). Social norms and energy conservation. *Journal of public Economics, 95*(9-10), 1082-1095. https://doi.org/10.1016/j.jpubeco.2011.03.003

Allpress, J. A., Brown, R., Giner-Sorolla, R., Deonna, J. A., & Teroni, F. (2014). Two faces of group-based shame: Moral shame and image shame differentially predict positive and negative orientations to ingroup wrongdoing. *Personality and Social Psychology Bulletin*, *40*(10), 1270-1284. https://doi.org/10.1177/0146167214540724

Aloe, A. M. (2015). Inaccuracy of regression results in replacing bivariate correlations. *Research Synthesis Methods, 6*(1), 21-27. https://doi.org/10.1002/jrsm.1126

Andreoni, J. (1990). Impure altruism and donations to public goods: A theory of warm-glow giving. *The economic journal*, *100*(401), 464-477. https://doi.org/10.2307/2234133

Arroyo, P., & Carrete, L. (2019). Motivational drivers for the adoption of green energy: The case of purchasing photovoltaic systems. *Management Research Review*, *42*(5), 542-567. https://doi.org/10.1108/MRR-02-2018-0070

Asch, S. E. (1951). Effects of group pressure upon the modification distortion of judgments. In H. Guetzkow (Ed.), *Groups, leadership and men* (pp. 177-190). Carnegie Press.

Ashworth, P., Sun, Y., Ferguson, M., Witt, K., & She, S. (2019). Comparing how the public perceive CCS across Australia and China. *International Journal of Greenhouse Gas Control*, *86*, 125-133. https://doi.org/10.1016/j.ijggc.2019.04.008

Bamberg, S., & Möser, G. (2007). Twenty years after Hines, Hungerford, and Tomera: A new meta-analysis of psycho-social determinants of pro-environmental behaviour. *Journal of Environmental Psychology*, *27*(1), 14–25. https://doi.org/10.1016/j.jenvp.2006.12.002

Barnett, J., Burningham, K., Walker, G., & Cass, N. (2012). Imagined publics and engagement around renewable energy technologies in the UK. *Public Understanding of Science, 21*(1), 36-50. https://doi.org/10.1177/0963662510365663

Barth, M., Jugert, P., & Fritsche, I. (2016). Still underdetected–Social norms and collective efficacy predict the acceptance of electric vehicles in Germany. *Transportation research part F: traffic psychology and behaviour*, *37*, 64-77. https://doi.org/10.1016/j.trf.2015.11.011

Bashiri, A., & Alizadeh, S. H. (2018). The analysis of demographics, environmental and knowledge factors affecting prospective residential PV system adoption: A study in Tehran. *Renewable and Sustainable Energy Reviews, 81*, 3131-3139. https://doi.org/10.1016/j.rser.2017.08.093

Batel, S. (2020). Research on the social acceptance of renewable energy technologies: Past, present and future. *Energy Research & Social Science*, *68*, 101544. https://doi.org/10.1016/j.erss.2020.101544

Batel, S., Castro, P., Devine-Wright, P., & Howarth, C. (2016). Developing a critical agenda to understand pro-environmental actions: contributions from Social Representations and Social Practices Theories. *Wiley Interdisciplinary Reviews: Climate Change*, *7*(5), 727-745. https://doi.org/10.1002/wcc.417

Baum, C. M., Low, S., & Sovacool, B. K. (2022). Between the sun and us: Expert perceptions on the innovation, policy, and deep uncertainties of space-based solar geoengineering. *Renewable and Sustainable Energy Reviews*, *158*, 112179. https://doi.org/10.1016/j.rser.2022.112179

Baumeister, R. F., Vohs, K. D., Nathan DeWall, C., & Zhang, L. (2007). How emotion shapes behavior: Feedback, anticipation, and reflection, rather than direct causation. *Personality and social psychology review*, *11*(2), 167-203. https://doi.org/10.1177/1088868307301033

Baur, D., Emmerich, P., Baumann, M. J., & Weil, M. (2022). Assessing the social acceptance of key technologies for the German energy transition. *Energy, Sustainability and Society*, *12*(1), 1-16. https://doi.org/10.1186/s13705-021-00329-x

Bergquist, M., Nilsson, A., & Schultz, W. P. (2019). A meta-analysis of field-experiments using social norms to promote pro-environmental behaviors. *Global Environmental Change*, *59*, 101941. https://doi.org/10.1016/j.gloenvcha.2019.101941

Bergquist, M., Thiel, M., Goldberg, M. H., & van der Linden, S. (2023). Field interventions for climate change mitigation behaviors: A second-order meta-analysis. *Proceedings of the National Academy of Sciences*, *120*(13), e2214851120. https://doi.org/10.1073/pnas.2214851120

Bessette, D., & Crawford, J. (2022). All's fair in love and WAR: The conduct of wind acceptance research (WAR) in the United States and Canada. *Energy Research & Social Science, 88,* 102514. https://doi.org/10.1016/j.erss.2022.102514

Bhushan, N., Mohnert, F., Sloot, D., Jans, L., Albers, C., & Steg, L. (2019). Using a Gaussian graphical model to explore relationships between items and variables in environmental psychology research. *Frontiers in psychology, 10*, 1050. https://doi.org/10.3389/fpsyg.2019.01050

Bicchieri, C., Xiao, E., & Muldoon, R. (2011). Trustworthiness is a social norm, but trusting is not. *Politics, Philosophy & Economics, 10*(2), 170-187. https://doi.org/10.1177/1470594X10387260

Bidwell, D. (2013). The role of values in public beliefs and attitudes towards commercial wind energy. *Energy Policy, 58*, 189-199. https://doi.org/10.1016/j.enpol.2013.03.010

Bidwell, D. (2023). Tourists are people too: Nonresidents' values, beliefs, and acceptance of a nearshore wind farm. *Energy Policy, 173*, 113365. https://doi.org/10.1016/j.enpol.2022.113365

Bissing-Olson, M. J., Fielding, K. S., & Iyer, A. (2016). Experiences of pride, not guilt, predict pro-environmental behavior when pro-environmental descriptive norms are more positive. *Journal of Environmental Psychology, 45*, 145-153. https://doi.org/10.1016/j.jenvp.2016.01.001

Bollinger, B., & Gillingham, K. (2012). Peer effects in the diffusion of solar photovoltaic panels. *Marketing Science, 31*(6), 900-912. https://doi.org/10.1287/mksc.1120.0727

Bonaiuto, M. (2023). Psicologia sociale della transizione ecologica [Social psychology of ecological transition]. In D.G. Myers, J.M. Twenge, E. Marta, & M. Pozzi (Eds.), *Psicologia Sociale* [Social Psychology] (4th ed., pp. 483-519). McGraw-Hill Education.

Bonaiuto, M., Dessi, F., & Ariccio, S. (2023). Acceptability, acceptance, and adoption of renewable and sustainable energy technologies. In *Sustainability and ecological transition in the post-Covid era. Challenges and opportunities in the face of climate change and energy* *transition* (pp. 41-61). Institute of Psychosocial Studies and Research "Xoan Vicente Viqueira".

Bonaiuto, M., Mosca, O., Milani, A., Ariccio, S., Dessi, F., & Fornara, F. (2024). Beliefs about technological and contextual features drive biofuels' social acceptance. *Renewable and Sustainable Energy Reviews*, *189*, 113867. https://doi.org/10.1016/j.rser.2023.113867

Bonan, J., Cattaneo, C., d'Adda, G., & Tavoni, M. (2020). The interaction of descriptive and injunctive social norms in promoting energy conservation. *Nature Energy*, *5*(11), 900-909. https://doi.org/10.1038/s41560-020-00719-z

Borenstein, M., Hedges, L. V., Higgins, J. P., & Rothstein, H. R. (2021). *Introduction to meta-analysis*. Wileys.

Box, G. E., & Cox, D. R. (1964). An analysis of transformations. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *26*(2), 211-243. https://doi.org/10.1111/j.2517-6161.1964.tb00553.x

Brunson, M. W., & Shindler, B. A. (2004). Geographic variation in social acceptability of wildland fuels management in the western United States. *Society and Natural Resources*, *17*(8), 661-678. https://doi.org/10.1080/08941920490480688

Busse, M., & Siebert, R. (2018). Acceptance studies in the field of land use—A critical and systematic review to advance the conceptualization of acceptance and acceptability. *Land use policy*, *76*, 235-245. https://doi.org/10.1016/j.landusepol.2018.05.016

Capodaglio, A. G., Callegari, A., & Lopez, M. V. (2016). European framework for the diffusion of biogas uses: emerging technologies, acceptance, incentive strategies, and institutional-regulatory support. *Sustainability*, *8*(4), 298. https://doi.org/10.3390/su8040298

Card, N.A. (2015). *Applied meta-Analysis for Social Science Research*. Guilford Press.

Carlman, I. (1984). The views of politicians and decision-makers on planning for the use of wind power in Sweden. *European Wind Energy Conference*, 22–36.

Cass, N., & Walker, G. (2009). Emotion and rationality: The characterisation and evaluation of opposition to renewable energy projects. *Emotion, Space and Society*, *2*(1), 62-69. https://doi.org/10.1016/j.emospa.2009.05.006

Cass, N., Walker, G., & Devine-Wright, P. (2010). Good neighbours, public relations and bribes: the politics and perceptions of community benefit provision in renewable energy development in the UK. *Journal of environmental policy & planning*, *12*(3), 255-275. https://doi.org/10.1080/1523908X.2010.509558

Chan, H. W., Udall, A. M., & Tam, K. P. (2022). Effects of perceived social norms on support for renewable energy transition: Moderation by national culture and environmental risks. *Journal of Environmental Psychology*, *79*, 101750. https://doi.org/10.1016/j.jenvp.2021.101750

Chen, C. F., Xu, X., & Frey, S. (2016). Who wants solar water heaters and alternative fuel vehicles? Assessing social–psychological predictors of adoption intention and policy support in China. *Energy Research & Social Science*, *15*, 1-11. https://doi.org/10.1016/j.erss.2016.02.006

Cialdini, R. B., & Goldstein, N. J. (2004). Social influence: Compliance and conformity. *Annual Review of Psychology*, *55*(1), 591-621. https://doi.org/10.1146/annurev.psych.55.090902.142015

Cialdini, R. B., & Jacobson, R. P. (2021). Influences of social norms on climate change-related behaviors. *Current Opinion in Behavioral Sciences*, *42*, 1–8. https://doi.org/10.1016/j.cobeha.2021.01.005

Cialdini, R. B., Kallgren, C. A., & Reno, R. R. (1991). A focus theory of normative conduct: A theoretical refinement and reevaluation of the role of norms in human behavior. *Advances in experimental social psychology*, *24*, 201-234. https://doi.org/10.1016/S0065-2601(08)60330-5

Cialdini, R. B., Reno, R. R., & Kallgren, C. A. (1990). A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. *Journal of personality and social psychology*, *58*(6), 1015. https://psycnet.apa.org/doi/10.1037/0022-3514.58.6.1015

Clayton, S., Devine-Wright, P., Stern, P. C., Whitmarsh, L., Carrico, A., Steg, L., ... & Bonnes, M. (2015). Psychological research and global climate change. *Nature climate change*, *5*(7), 640-646. https://doi.org/10.1038/nclimate2622

Cohen, J. (1992). A power primer, *Psychological Bulletin*, *112*, 155–159.

Cologna, V., & Siegrist, M. (2020). The role of trust for climate change mitigation and adaptation behaviour: A meta-analysis. *Journal of Environmental Psychology*, *69*, 101428. https://doi.org/10.1016/j.jenvp.2020.101428

Conte, B., Hahnel, U. J., & Brosch, T. (2023). From values to emotions: Cognitive appraisal mediates the impact of core values on emotional experience. *Emotion*, *23*(4), 1115. https://doi.org/10.1037/emo0001083

Cook, R.D., & Weisberg, S. (1982). *Residuals and Influence in Regression*. Chapman and Hall.

Contzen, N., Perlaviciute, G., Steg, L., Reckels, S. C., Alves, S., Bidwell, D., ... & Sütterlin, B. (2024). Public opinion about solar radiation management: A cross-cultural study in 20 countries around the world. *Climatic Change*, *177*(4), 65. https://doi.org/10.1007/s10584-024-03708-3

Corner, A., & Pidgeon, N. (2010). Geoengineering the climate: the social and ethical implications. *Environment: Science and Policy for Sustainable Development, 52(*1), 24-37. https://doi.org/10.1080/00139150903479563

Constantino, S. M., Sparkman, G., Kraft-Todd, G. T., Bicchieri, C., Centola, D., Shell-Duncan, B., ... & Weber, E. U. (2022). Scaling up change: a critical review and practical guide to harnessing social norms for climate action. *Psychological science in the public interest*, *23*(2), 50-97. https://doi.org/10.1177/15291006221105279

Cousse, J. (2021). Still in love with solar energy? Installation size, affect, and the social acceptance of renewable energy technologies. *Renewable and Sustainable Energy Reviews*, *145*, 111107. https://doi.org/10.1016/j.rser.2021.111107

Cousse, J., Trutnevyte, E., & Hahnel, U. J. (2021). Tell me how you feel about geothermal energy: Affect as a revealing factor of the role of seismic risk on public acceptance. *Energy Policy*, *158*, 112547. https://doi.org/10.1016/j.enpol.2021.112547

Cousse, J., Wüstenhagen, R., & Schneider, N. (2020). Mixed feelings on wind energy: Affective imagery and local concern driving social acceptance in Switzerland. *Energy research & social science*, *70*, 101676. https://doi.org/10.1016/j.erss.2020.101676

Curtius, H. C., Hille, S. L., Berger, C., Hahnel, U. J. J., & Wüstenhagen, R. (2018). Shotgun or snowball approach? Accelerating the diffusion of rooftop solar photovoltaics through peer effects and social norms. *Energy policy*, *118*, 596-602. https://doi.org/10.1016/j.enpol.2018.04.005

Dalege, J., Borsboom, D., Van Harreveld, F., Van den Berg, H., Conner, M., & Van der Maas, H. L. (2016). Toward a formalized account of attitudes: The Causal Attitude Network (CAN) model. *Psychological review*, *123*(1), 2. https://doi.org/10.1037/a0039802

Dalege, J., Borsboom, D., van Harreveld, F., & van der Maas, H. L. (2019). A network perspective on attitude strength: Testing the connectivity hypothesis. *Social Psychological and Personality Science*, *10*(6), 746-756. https://doi.org/10.1177/1948550618781062

Dalege, J., Borsboom, D., van Harreveld, F., Waldorp, L. J., & van der Maas, H. L. (2017). Network structure explains the impact of attitudes on voting decisions. *Scientific reports*, *7*(1), 4909. https://doi.org/10.1038/s41598-017-05048-y

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). Technology acceptance model. *Journal of management sciences, 35*(8), 982-1003.

De Groot, J. I., Bondy, K., & Schuitema, G. (2021). Listen to others or yourself? The role of personal norms on the effectiveness of social norm interventions to change pro-environmental behavior. *Journal of Environmental Psychology*, *78*, 101688. https://doi.org/10.1016/j.jenvp.2021.101688

De Groot, J. I., & Schuitema, G. (2012). How to make the unpopular popular? Policy characteristics, social norms and the acceptability of environmental policies. *Environmental Science & Policy*, *19*, 100-107. https://doi.org/10.1016/j.envsci.2012.03.004

De Groot, J. I., & Steg, L. (2010). Morality and nuclear energy: Perceptions of risks and benefits, personal norms, and willingness to take action related to nuclear energy. *Risk Analysis: An International Journal*, *30*(9), 1363-1373. https://doi.org/10.1111/j.1539-6924.2010.01419.x

De Groot, J. I., Steg, L., & Poortinga, W. (2013). Values, perceived risks and benefits, and acceptability of nuclear energy. *Risk Analysis: An International Journal*, *33*(2), 307-317. https://doi.org/10.1111/j.1539-6924.2012.01845.x de Hooge, I. E., Zeelenberg, M., & Breugelmans, S. M. (2010). Restore and protect motivations following shame. *Cognition & Emotion, 24*(1), 111–127. https://doi.org/10.1080/02699930802584466

De Luca, E., Zini, A., Amerighi, O., Coletta, G., Oteri, M. G., Giuffrida, L. G., & Graditi, G. (2020). A technology evaluation method for assessing the potential contribution of energy technologies to decarbonisation of the Italian production system. *International Journal of Sustainable Energy Planning and Management*, *29*, 41-56. https://doi.org/10.5278/ijsepm.4433

Dessi, F., Ariccio, S., Albers, T., Alves, S., Ludovico, N., & Bonaiuto, M. (2022). Sustainable technology acceptability: Mapping technological, contextual, and social-psychological determinants of EU stakeholders' biofuel acceptance. *Renewable and Sustainable Energy Reviews*, *158*, 112114. https://doi.org/10.1016/j.rser.2022.112114

Devine-Wright, P. (2005). Beyond NIMBYism: towards an integrated framework for understanding public perceptions of wind energy. *Wind Energy 8*(2), 125-139. https://doi.org/10.1002/we.124

Devine-Wright, P. (2009). Rethinking NIMBYism: The role of place attachment and place identity in explaining place-protective action. *Journal of community & applied social psychology*, *19*(6), 426-441. https://doi.org/10.1002/casp.1004

Devine-Wright, P. (2022). Decarbonisation of industrial clusters: a place-based research agenda. *Energy Research & Social Science*, *91*, 102725. https://doi.org/10.1016/j.erss.2022.102725

Diel, K., & Friese, M. (2024). Morally charged: Why people prefer to compare themselves with others who are less environmentally friendly than themselves. *Journal of Environmental Psychology*, *96*, 102318. https://doi.org/10.1016/j.jenvp.2024.102318

Diel, K., Broeker, L., Raab, M., & Hofmann, W. (2021). Motivational and emotional effects of social comparison in sports. *Psychology of Sport and Exercise*, *57*, 102048. https://doi.org/10.1016/j.psychsport.2021.102048

Diel, K., Grelle, S., & Hofmann, W. (2021). A motivational framework of social comparison. *Journal of Personality and Social Psychology*, *120*(6), 1415. https://doi.org/10.1037/pspa0000204

Duval, S., & Tweedie, R. (2000). A nonparametric "trim and fill" method of accounting for publication bias in meta-analysis. *Journal of the american statistical association*, *95*(449), 89-98. https://doi.org/10.1080/01621459.2000.10473905

Egger, B., Klaefiger, Y., Theis, A., & Salzburger, W. (2011). A sensory bias has triggered the evolution of egg-spots in cichlid fishes. *PLoS one*, *6*(10), e25601. https://doi.org/10.1371/journal.pone.0025601

Egger, M., Smith, G. D., Schneider, M., & Minder, C. (1997). Bias in meta-analysis detected by a simple, graphical test. *British Medical Journal*, *315*(7109), 629-634. https://doi.org/10.1136/bmj.315.7109.629

Epskamp, S., Cramer, A. O., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph: Network visualizations of relationships in psychometric data. *Journal of statistical software*, *48*, 1-18. https://doi.org/10.18637/jss.v048.i04

Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological methods*, *23*(4), 617. Retrieved from: https://arxiv.org/pdf/1607.01367

Ertz, M., Karakas, F., & Sarigöllü, E. (2016). Exploring pro-environmental behaviors of consumers: An analysis of contextual factors, attitude, and behaviors. *Journal of business research*, *69*(10), 3971-3980. https://doi.org/10.1016/j.jbusres.2016.06.010

Farrow, K., Grolleau, G., & Ibanez, L. (2017). Social norms and pro-environmental behavior: A review of the evidence. *Ecological Economics, 140,* 1-13. https://doi.org/10.1016/j.ecolecon.2017.04.017

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior research methods*, *39*(2), 175-191. https://doi.org/10.3758/BF03193146

Fessler, D. M. T. (2007). From appeasement to conformity: Evolutionary and cultural perspectives on shame, competition, and cooperation. In J. L. Tracy, R. W. Robins, & J. P. Tangney (Eds.), *The selfconscious emotions: Theory and research* (pp. 174–193). Guilford Press.

Festinger, L. (1954). A theory of social comparison processes. *Human relations*, *7*(2), 117-140. https://doi.org/10.1177/001872675400700202

Field, A. (2009). *Discovering statistics using SPSS*. SAGE Publications.

Fischhoff, B., Slovic, P., Lichtenstein, S., Read, S., & Combs, B. (1978). How safe is safe enough? A psychometric study of attitudes towards technological risks and benefits. *Policy sciences*, *9*, 127-152. https://doi.org/10.1007/BF00143739

Fornara, F., Pattitoni, P., Mura, M., & Strazzera, E. (2016). Predicting intention to improve household energy efficiency: The role of value-belief-norm theory, normative and informational influence, and specific attitude. *Journal of environmental psychology*, *45*, 1-10. https://doi.org/10.1016/j.jenvp.2015.11.001

Fournis, Y., & Fortin, M. J. (2017). From social "acceptance" to social "acceptability" of wind energy projects: towards a territorial perspective. *Journal of environmental planning and management*, *60*(1), 1-21. https://doi.org/10.1080/09640568.2015.1133406

Francis, J. J., Johnston M, Eccles M, Walker A, Grimshaw, J. M., Foy, R., Kaner, E. F. S., Smith, L. & Bonetti, D. (2004). *Constructing questionnaires based on the theory of planned behaviour: a manual for health services researchers. In: Quality of life and management of living resources: Centre for: Health Services Research*; 2004 Centre for Health Services Research, University of Newcastle upon Tyne, United Kingdom. Retrived from: https://openaccess.city.ac.uk/id/eprint/1735/

Franco, A., Malhotra, N., & Simonovits, G. (2014). Publication bias in the social sciences: Unlocking the file drawer. *Science*, *345*(6203), 1502-1505. https://doi.org/10.1126/science.1255484

Fransen, M. L., Smit, E. G., & Verlegh, P. W. (2015). Strategies and motives for resistance to persuasion: An integrative framework. *Frontiers in psychology*, *6*, 1201. https://doi.org/10.3389/fpsyg.2015.01201

Freudenberg, N., & Steinsapir, C. (1991). Not in our backyards: The grassroots environmental movement. *Society & Natural Resources*, *4*(3), 235-245. https://doi.org/10.1080/08941929109380757

Fu, R., Gartlehner, G., Grant, M., Shamliyan, T., Sedrakyan, A., Wilt, T. J., ... & Trikalinos, T. A. (2011). Conducting quantitative synthesis when comparing medical interventions: AHRQ and the Effective Health Care Program. *Journal of clinical epidemiology*, *64*(11), 1187-1197. https://doi.org/10.1016/j.jclinepi.2010.08.010

Fytili, D., & Zabaniotou, A. (2017). Social acceptance of bioenergy in the context of climate change and sustainability–A review. *Current opinion in green and sustainable chemistry*, *8*, 5-9. https://doi.org/10.1016/j.cogsc.2017.07.006

Gaede, J., & Rowlands, I. H. (2018). Visualizing social acceptance research: A bibliometric review of the social acceptance literature for energy technology and fuels. *Energy research & social science*, *40*, 142-158. https://doi.org/10.1016/j.erss.2017.12.006

Garson, G. D. (2012). *Testing statistical Assumptions*. Statistical Associates Publishing.

Gelfand, M. J., Nishii, L. H., & Raver, J. L. (2006). On the nature and importance of cultural tightness-looseness. *Journal of applied psychology*, *91*(6), 1225.

Gelfand, M. J., Raver, J. L., Nishii, L., Leslie, L. M., Lun, J., Lim, B. C., ... & Yamaguchi, S. (2011). Differences between tight and loose cultures: A 33-nation study. *Science*, *332*(6033), 1100-1104. https://doi.org/10.1126/science.1197754

Geiger, J. L., Steg, L., Van Der Werff, E., & Ünal, A. B. (2019). A meta-analysis of factors related to recycling. *Journal of environmental psychology*, *64*, 78-97. https://doi.org/10.1016/j.jenvp.2019.05.004

Gifford, R. (2011). The dragons of inaction: psychological barriers that limit climate change mitigation and adaptation. *American psychologist*, *66*(4), 290-302. https://doi.org/10.1037/a0023566

Gifford, R., & Nilsson, A. (2014). Personal and social factors that influence pro-environmental concern and behaviour: A review. *International journal of psychology*, *49*(3), 141-157. https://doi.org/10.1002/ijop.12034

Gilbert P., McEwan K., Mitra R., Franks L., Richter A., Rockliff H. (2008). Feeling safe and content: A specific affect regulation system? Relationship to depression, anxiety, stress, and self-criticism. *The Journal of Positive Psychology*, *3*(3), 182–191. https://doi.org/10.1080/17439760801999461

Goldthau, A., & Sovacool, B. K. (2012). The uniqueness of the energy security, justice, and governance problem. *Energy policy*, *41*, 232-240. https://doi.org/10.1016/j.enpol.2011.10.042

Gölz, S., & Wedderhoff, O. (2018). Explaining regional acceptance of the German energy transition by including trust in stakeholders and perception of fairness as socio-institutional factors. *Energy Research & Social Science*, *43*, 96-108. https://doi.org/10.1016/j.erss.2018.05.026

Gracia, A., Barreiro-Hurlé, J., & y Pérez, L. P. (2018). Overcoming the barriers for biodiesel use in Spain: an analysis of the role of convenience and price. *Journal of cleaner production*, *172*, 391-401. https://doi.org/10.1016/j.jclepro.2017.10.013

Gray, J. A. (1990). Brain systems that mediate both emotion and cognition. *Cognition and Emotion*, *4*, 269-288. https://doi.org/10.1080/02699939008410799

Graziano, M., & Gillingham, K. (2015). Spatial patterns of solar photovoltaic system adoption: the influence of neighbors and the built environment. *Journal of Economic Geography*, *15*(4), 815-839. https://doi.org/10.1093/jeg/lbu036

Griskevicius, V., Tybur, J. M., & Van den Bergh, B. (2010). Going green to be seen: status, reputation, and conspicuous conservation. *Journal of personality and social psychology*, *98*(3), 392. https://psycnet.apa.org/doi/10.1037/a0017346

Haddaway, N. R., Woodcock, P., Macura, B., & Collins, A. (2015). Making literature reviews more reliable through application of lessons from systematic reviews. *Conservation Biology*, *29*(6), 1596-1605. https://doi.org/10.1111/cobi.12541

Halder, P., Pietarinen, J., Havu-Nuutinen, S., Pöllänen, S., & Pelkonen, P. (2016). The Theory of Planned Behavior model and students' intentions to use bioenergy: A cross-cultural perspective. *Renewable Energy*, *89*, 627-635. https://doi.org/10.1016/j.renene.2015.12.023

Han, H. (2014). The norm activation model and theory-broadening: Individuals' decision-making on environmentally-responsible convention attendance. *Journal of environmental psychology*, *40*, 462-471. https://doi.org/10.1016/j.jenvp.2014.10.006

Hardin, G. (1968). The tragedy of the commons: the population problem has no technical solution; it requires a fundamental extension in morality. *Science*, *162*(3859), 1243-1248. https://doi.org/10.1126/science.162.3859.1243

Harland, P., Staats, H., & Wilke, H. A. (1999). Explaining proenvironmental intention and behavior by personal norms and the Theory of Planned Behavior. *Journal of applied social psychology*, *29*(12), 2505-2528. https://doi.org/10.1111/j.1559-1816.1999.tb00123.x

Hartmann, P., Eisend, M., Apaolaza, V., & D'Souza, C. (2017). Warm glow vs. altruistic values: How important is intrinsic emotional reward in proenvironmental behavior?. *Journal of Environmental Psychology*, *52*, 43-55. https://doi.org/10.1016/j.jenvp.2017.05.006

Hayes, A. F. (2017). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach.* Guilford Press.

Héder, M. (2017). From NASA to EU: the evolution of the TRL scale in Public Sector Innovation. *The Innovation Journal*, *22*(2), 1-23.

Hedges, L. V., & Pigott, T. D. (2004). The power of statistical tests for moderators in meta-analysis. *Psychological methods*, *9*(4), 426. https://doi.org/10.1037/1082-989X.9.4.426

Higgins, J. P., & Thompson, S. G. (2002). Quantifying heterogeneity in a meta-analysis. *Statistics in medicine*, *21*(11), 1539-1558. https://doi.org/10.1002/sim.1186

Horne, C., Kennedy, E. H., & Familia, T. (2021). Rooftop solar in the United States: Exploring trust, utility perceptions, and adoption among California homeowners. *Energy Research & Social Science*, *82*, 102308. https://doi.org/10.1016/j.erss.2021.102308

Hornsey, M. J., Harris, E. A., Bain, P. G., & Fielding, K. S. (2016). Meta-analyses of the determinants and outcomes of belief in climate change. *Nature climate change*, *6*(6), 622-626. https://doi.org/10.1038/nclimate2943

Huijts, N. M., Molin, E. J., & Steg, L. (2012). Psychological factors influencing sustainable energy technology acceptance: A review-based comprehensive framework. Renewable and sustainable energy reviews, *16*(1), 525-531. https://doi.org/10.1016/j.rser.2011.08.018

Huijts, N. M., Molin, E. J., & van Wee, B. (2014). Hydrogen fuel station acceptance: A structural equation model based on the technology acceptance framework. *Journal of Environmental Psychology*, *38*, 153-166. https://doi.org/10.1016/j.jenvp.2014.01.008

Ioannidis, J. P., Patsopoulos, N. A., & Evangelou, E. (2007). Uncertainty in heterogeneity estimates in meta-analyses. *British Medical Journal, 335*(7626), 914-916. https://doi.org/10.1136/bmj.39343.408449.80

IPCC (2014). Summary for Policymakers. In *Climate Change 2014: Synthesis Report*. [Contribution of Working Groups I, II and III to the Fifth assessment report of the Intergovernmental Panel on Climate Change].

IPCC (2018). *Global warming of 1.5°C* [Special report].

IPCC (2021). Summary for Policymakers. In *Climate Change 2021: The Physical Science Basis.* [Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change].

IPCC (2022). Summary for Policymakers. In *Climate Change 2022: Mitigation of Climate Change.* [Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change].

IPCC (2023). Summary for Policymakers. In *Climate Change 2023: Synthesis Report.* [Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change].

Irfan, M., Zhao, Z. Y., Rehman, A., Ozturk, I., & Li, H. (2021). Consumers' intention-based influence factors of renewable energy adoption in Pakistan: a structural equation modeling approach. *Environmental Science and Pollution Research*, *28*, 432-445. https://doi.org/10.1007/s11356-020-10504-w

Kalkbrenner, B. J., & Roosen, J. (2016). Citizens' willingness to participate in local renewable energy projects: The role of community and trust in Germany. *Energy Research & Social Science*, *13*, 60-70. https://doi.org/10.1016/j.erss.2015.12.006

Keller, C., Visschers, V., & Siegrist, M. (2012). Affective imagery and acceptance of replacing nuclear power plants. *Risk Analysis: An International Journal*, *32*(3), 464-477. https://doi.org/10.1111/j.1539-6924.2011.01691.x

Kim, E. H. (2013). Deregulation and differentiation: Incumbent investment in green technologies. *Strategic Management Journal*, *34*(10), 1162-1185. https://doi.org/10.1002/smj.2067

Kim, S., Lee, J. E., & Kim, D. (2019). Searching for the next new energy in energy transition: Comparing the impacts of economic incentives on local acceptance of fossil fuels, renewable, and nuclear energies. *Sustainability*, *11*(7), 2037. https://doi.org/10.3390/su11072037

Klaus, G., Ernst, A., & Oswald, L. (2020). Psychological factors influencing laypersons' acceptance of climate engineering, climate change mitigation and business as usual scenarios. *Technology in Society*, *60*, 101222. https://doi.org/10.1016/j.techsoc.2019.101222

Köhler, J., Geels, F. W., Kern, F., Markard, J., Onsongo, E., Wieczorek, A., ... & Wells, P. (2019). An agenda for sustainability transitions research: State of the art and future directions. *Environmental innovation and societal transitions*, *31*, 1-32.

Kontopantelis, E., & Reeves, D. (2012). Performance of statistical methods for meta-analysis when true study effects are non-normally distributed: a simulation study. *Statistical methods in medical research*, *21*(4), 409-426. https://doi.org/10.1177/0962280210392008

Korcaj, L., Hahnel, U. J., & Spada, H. (2015). Intentions to adopt photovoltaic systems depend on homeowners' expected personal gains and behavior of peers. *Renewable Energy*, *75*, 407-415. https://doi.org/10.1016/j.renene.2014.10.007

Kowalska-Pyzalska, A. (2018). What makes consumers adopt to innovative energy services in the energy market? A review of incentives and barriers. *Renewable and Sustainable Energy Reviews*, *82*, 3570-3581. https://doi.org/10.1016/j.rser.2017.10.103

Krueger, J. I., Massey, A. L., & DiDonato, T. E. (2008). A matter of trust: From social preferences to the strategic adherence to social norms. *Negotiation and Conflict Management Research*, *1*(1), 31-52. https://doi.org/10.1111/j.1750-4716.2007.00003.x

Kuppens, T., & Yzerbyt, V. Y. (2012). Group-based emotions: The impact of social identity on appraisals, emotions, and behaviors. *Basic and applied social psychology*, *34*(1), 20-33. https://doi.org/10.1080/01973533.2011.637474

Lazarus R. S. (1991). *Emotion and adaptation*. Oxford University Press.

Lennon, B., Dunphy, N. P., & Sanvicente, E. (2019). Community acceptability and the energy transition: A citizens' perspective. *Energy, Sustainability and Society*, *9*(1), 1-18. https://doi.org/10.1186/s13705-019-0218-z

Li, J., Chen, C. F., Walzem, A., Nelson, H., & Shuai, C. (2022). National goals or sense of community? Exploring the social-psychological influence of household solar energy adoption in rural China. *Energy Research & Social Science*, *89*, 102669. https://doi.org/10.1016/j.erss.2022.102669

Lindenberg, S., & Steg, L. (2007). Normative, gain and hedonic goal frames guiding environmental behavior. *Journal of Social issues*, *63*(1), 117-137. https://doi.org/10.1111/j.1540-4560.2007.00499.x

Liu, B., Xu, Y., Yang, Y., & Lu, S. (2021). How public cognition influences public acceptance of CCUS in China: Based on the ABC (affect, behavior, and cognition) model of attitudes. *Energy Policy*, *156*, 112390. https://doi.org/10.1016/j.enpol.2021.112390

Liu, L., Bouman, T., Perlaviciute, G., & Steg, L. (2019). Effects of trust and public participation on acceptability of renewable energy projects in the Netherlands and China. *Energy Research & Social Science*, *53*, 137-144. https://doi.org/10.1016/j.erss.2019.03.006

Liu, L., Bouman, T., Perlaviciute, G., & Steg, L. (2020a). Public participation in decision making, perceived procedural fairness and public acceptability of renewable energy projects. *Energy and Climate Change*, *1*, 100013. https://doi.org/10.1016/j.egycc.2020.100013

Liu, L., Bouman, T., Perlaviciute, G., & Steg, L. (2020b). Effects of competence-and integrity-based trust on public acceptability of renewable energy projects in China and the Netherlands. *Journal of Environmental Psychology*, *67*, 101390. https://doi.org/10.1016/j.jenvp.2020.101390

Lomax, R. G., & Hahs-Vaughn, D. L. (2012). *An introduction to statistical concepts* (3rd Ed.). Taylors and Francis.

Low, S., Baum, C. M., & Sovacool, B. K. (2022). Rethinking Net-Zero systems, spaces, and societies: “Hard” versus “soft” alternatives for nature-based and engineered carbon removal. *Global Environmental Change*, *75*, 102530. https://doi.org/10.1016/j.gloenvcha.2022.102530

Low, S., Fritz, L., Baum, C. M., & Sovacool, B. K. (2024). Public perceptions on carbon removal from focus groups in 22 countries. *Nature Communications*, *15*(1), 3453. https://doi.org/10.1038/s41467-024-47853-w

Mackinnon, A., Jorm, A. F., Christensen, H., Korten, A. E., Jacomb, P. A., & Rodgers, B. (1999). A short form of the Positive and Negative Affect Schedule: Evaluation of factorial validity and invariance across demographic variables in a community sample. *Personality and Individual differences*, *27*(3), 405-416. https://doi.org/10.1016/S0191-8869(98)00251-7

Mallett, R. K., Melchiori, K. J., & Strickroth, T. (2013). Self-confrontation via a carbon footprint calculator increases guilt and support for a proenvironmental group. *Ecopsychology*, *5*(1), 9-16. https://doi.org/10.1089/eco.2012.0067

Marangunić, N., & Granić, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. *Universal access in the information society*, *14*, 81-95. https://doi.org/10.1007/s10209-014-0348-1

Masukujjaman, M., Alam, S. S., Siwar, C., & Halim, S. A. (2021). Purchase intention of renewable energy technology in rural areas in Bangladesh: Empirical evidence. *Renewable Energy*, *170*, 639-651. https://doi.org/10.1016/j.renene.2021.01.125

McDonald, R. I., Fielding, K. S., & Louis, W. R. (2013). Energizing and de-motivating effects of norm conflict. *Personality and Social Psychology Bulletin*, *39*, 57–72. https://doi.org/10.1177/0146167212464234

Međugorac, V., & Schuitema, G. (2023). Why is bottom-up more acceptable than top-down? A study on collective psychological ownership and place-technology fit in the Irish Midlands. *Energy Research & Social Science*, *96*, 102924. https://doi.org/10.1016/j.erss.2022.102924

Messerli, P., Murniningtyas, E., Eloundou-Enyegue, P., Foli, E. G., Furman, E., Glassman, A., ... & van Ypersele, J. P. (2019). Global sustainable development report 2019: the future is now–science for achieving sustainable development. Retrieved from: https://pure.iiasa.ac.at/id/eprint/16067/1/24797GSDR_report_2019.pdf

Meyer, W.-U., Reisenzein, R., & Schutzwohl, A. (1997). Towards a process analysis of emotions: The case of surprise. *Motivation and Emotion*, *21*, 251-274

Milani, A., Dessi, F., & Bonaiuto, M. (2024). A meta-analysis on the drivers and barriers to the social acceptance of renewable and sustainable energy technologies. *Energy Research & Social Science*, *114*, 103624. https://doi.org/10.1016/j.erss.2024.103624

Milani, A., Schultz, P. W., Packard, C. D., & Bonaiuto, M. (2024, August 29th). Social comparison and emotional reactions: The role of descriptive norms and emotions in influencing social acceptance of sustainable energy technologies. Retrieved from: osf.io/p9je8

Mill, J. S. (1863). *Utilitarianism*. Parker, Son, and Bourn.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & PRISMA Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *Annals of internal medicine*, *151*(4), 264-269. https://doi.org/10.7326/0003-4819-151-4-200908180-00135

Moynihan, A. B., & Schuitema, G. (2020). Values Influence Public Acceptability of Geoengineering Technologies Via Self-Identities. *Sustainability*, *12*(11), 4591. https://doi.org/10.3390/su12114591

Montijn-Dorgelo, F. N., & Midden, C. J. (2008). The role of negative associations and trust in risk perception of new hydrogen systems. *Journal of risk research*, *11*(5), 659-671. https://doi.org/10.1080/13669870801967218

Müller, S., & Rode, J. (2013). The adoption of photovoltaic systems in Wiesbaden, Germany. *Economics of Innovation and New Technology*, *22*(5), 519-535. https://doi.org/10.1080/10438599.2013.804333

Nasi, V. L., Jans, L., & Steg, L. (2023). Can we do more than "bounce back"? Transilience in the face of climate change risks. *Journal of Environmental Psychology*, *86*, 101947. https://doi.org/10.1016/j.jenvp.2022.101947

Neofytou, H., Nikas, A., & Doukas, H. (2020). Sustainable energy transition readiness: A multicriteria assessment index. *Renewable and Sustainable Energy Reviews*, *131*, 109988. https://doi.org/10.1016/j.rser.2020.109988

Neta, M., & Kim, M. J. (2023). Surprise as an emotion: a response to ortony. *Perspectives on Psychological Science*, *18*(4), 854-862. https://doi.org/10.1177/17456916221132789

Neves, C., Oliveira, T., & Santini, F. (2022). Sustainable technologies adoption research: A weight and meta-analysis. *Renewable and Sustainable Energy Reviews*, *165*, 112627. https://doi.org/10.1016/j.rser.2022.112627

Nielsen, M., Haun, D., Kärtner, J., & Legare, C. H. (2017). The persistent sampling bias in developmental psychology: A call to action. *Journal of experimental child psychology*, *162*, 31-38. https://doi.org/10.1016/j.jecp.2017.04.017

Nolan, J. M. (2021). Social norm interventions as a tool for pro-climate change. *Current Opinion in Psychology*, *42*, 120-125. https://doi.org/10.1016/j.copsyc.2021.06.001

Nolan, J. M., Schultz, P. W., Cialdini, R. B., Goldstein, N. J., & Griskevicius, V. (2008). Normative social influence is underdetected. *Personality and social psychology bulletin*, *34*(7), 913-923. https://doi.org/10.1177/0146167208316691

Noordewier, M. K., & Gocłowska, M. A. (2024). Shared and unique features of epistemic emotions: Awe, surprise, curiosity, interest, confusion, and boredom. *Emotion*, *24*(4), 1029. https://psycnet.apa.org/doi/10.1037/emo0001314

O'Garra, T., Mourato, S., & Pearson, P. (2008). Investigating attitudes to hydrogen refuelling facilities and the social cost to local residents. *Energy policy*, *36*(6), 2074-2085. https://doi.org/10.1016/j.enpol.2008.02.026

Oh, C. O., Nam, J., & Kim, H. (2023). The impacts of offshore wind farms on coastal Tourists' behaviors in South Korea. *Coastal Management*, *51*(1), 24-41. https://doi.org/10.1080/08920753.2023.2148848

Olejnik, S., & Algina, J. (2003). Generalized eta and omega squared statistics: measures of effect size for some common research designs. *Psychological methods*, *8*(4), 434. https://psycnet.apa.org/doi/10.1037/1082-989X.8.4.434

Onwezen, M. C., Bartels, J., & Antonides, G. (2014). The self-regulatory function of anticipated pride and guilt in a sustainable and healthy consumption context. *European Journal of Social Psychology*, *44*(1), 53–68. https://doi.org/10.1002/ejsp.1991

Ortony A. (2022). Are all "basic emotions" emotions? A problem for the (basic) emotions construct. *Perspectives on Psychological Science*, *17*(1), 41–61. https://doi.org/10.1177/1745691620985415

Ortony, A., & Russell, J. A. (2024). On the Invalidity of Neta and Kim's Argument That Surprise is Always Valenced. *Emotion Review*, *16*(1), 64-67. https://doi.org/10.1177/17540739231214785

Oyebode, B., & Nicholls, N. (2023). Social norms as anchor points for trust. *The Social Science Journal*, *60*(4), 744-754. https://doi.org/10.1080/03623319.2020.1753429

Packard, C. D., & Schultz, P. W. (2023). Emotions as the Enforcers of Norms. *Emotion Review*, *15*(4), 279-283. https://doi.org/10.1177/17540739231194315

Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & McKenzie, J. E. (2021). PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews. *British Medical Journal*, *372*. https://doi.org/10.1136/bmj.n160

Palomo-Vélez, G., Perlaviciute, G., Contzen, N., & Steg, L. (2021). Promoting energy sources as environmentally friendly: does it increase public acceptability?. *Environmental Research Communications*, *3*(11), 115004. https://doi.org/10.1088/2515-7620/ac32a8

Palomo-Vélez, G., Perlaviciute, G., Contzen, N., & Steg, L. (2024). Trusting the minister or trusting the mayor? Perceived competence and integrity of central and local Dutch institutions governing energy matters. *Environmental Research Communications*, *6*(4), 045009. https://doi.org/10.1088/2515-7620/ad3f7d

Payen, F. T., Moran, D., Cahurel, J. Y., Aitkenhead, M., Alexander, P., & MacLeod, M. (2022). Factors influencing winegrowers’ adoption of soil organic carbon sequestration practices in France. *Environmental Science & Policy*, *128*, 45-55. https://doi.org/10.1016/j.envsci.2021.11.011

Pedersen, E., & Persson Waye, K. (2004). Perception and annoyance due to wind turbine noise—a dose–response relationship. *The Journal of the Acoustical Society of America, 116*(6), 3460-3470. https://doi.org/10.1121/1.1815091

Perlaviciute, G., Görsch, R., Timmerman, M., Steg, L., & Vrieling, L. (2021). Values in the backyard: the relationship between people’s values and their evaluations of a real, nearby energy project. *Environmental Research Communications*, *3*(10), 105004. https://doi.org/10.1088/2515-7620/ac25d0

Perlaviciute, G., Schuitema, G., Devine-Wright, P., & Ram, B. (2018). At the heart of a sustainable energy transition: The public acceptability of energy projects. *IEEE Power and Energy Magazine, 16*(1), 49-55. https://doi.org/10.1109/MPE.2017.2759918

Perlaviciute, G., & Steg, L. (2014). Contextual and psychological factors shaping evaluations and acceptability of energy alternatives: Integrated review and research agenda. *Renewable and Sustainable Energy Reviews*, *35*, 361-381. https://doi.org/10.1016/j.rser.2014.04.003

Perlaviciute, G., & Steg, L. (2015). The influence of values on evaluations of energy alternatives. *Renewable energy*, *77*, 259-267. https://doi.org/10.1016/j.renene.2014.12.020

Perlaviciute, G., Steg, L., Contzen, N., Roeser, S., & Huijts, N. (2018). Emotional responses to energy projects: Insights for responsible decision making in a sustainable energy transition. *Sustainability*, *10*(7), 2526. https://doi.org/10.3390/su10072526

Perry, G. L., Richardson, S. J., Harré, N., Hodges, D., Lyver, P. O. B., Maseyk, F. J., ... & Brower, A. (2021). Evaluating the role of social norms in fostering pro-environmental behaviors. *Frontiers in Environmental Science*, *9*, 620125. https://doi.org/10.3389/fenvs.2021.620125

Peterson, R. A., & Brown, S. P. (2005). On the use of beta coefficients in meta-analysis. *Journal of applied psychology*, *90*(1), 175. https://doi.org/10.1037/0021-9010.90.1.175

Petty, R., & Cacioppo, J. (1986). The elaboration likelihood model of persuasion. *Advances in Experimental Social Psychology*, *19*, 123–205. https://doi.org/10.1016/S0065-2601(08)60214-2

Puzzolo, E., Pope, D., Stanistreet, D., Rehfuess, E. A., & Bruce, N. G. (2016). Clean fuels for resource-poor settings: A systematic review of barriers and enablers to adoption and sustained use. *Environmental research*, *146*, 218-234. https://doi.org/10.1016/j.envres.2016.01.002

Raju, P. S., Lonial, S. C., & Mangold, W. G. (1995). Differential effects of subjective knowledge, objective knowledge, and usage experience on decision making: An exploratory investigation. *Journal of consumer psychology*, *4*(2), 153-180. https://doi.org/10.1207/s15327663jcp0402_04

Reisenzein, R. (2000). The subjective experience of surprise. In H. Bless & J.P. Forgas (Eds.), *The message within: The role of subjective experience in social cognition and behavior* (pp. 262-279). Psychology Press.

Reisenzein, R., Horstmann, G., & Schützwohl, A. (2019). The cognitive-evolutionary model of surprise: A review of the evidence. *Topics in cognitive science*, *11*(1), 50-74. https://doi.org/10.1111/tops.12292

Rezaei, R., & Ghofranfarid, M. (2018). Rural households' renewable energy usage intention in Iran: Extending the unified theory of acceptance and use of technology. *Renewable energy*, *122*, 382-391. https://doi.org/10.1016/j.renene.2018.02.011

Rode, J., & Weber, A. (2016). Does localized imitation drive technology adoption? A case study on rooftop photovoltaic systems in Germany. *Journal of Environmental Economics and Management*, *78*, 38-48. https://doi.org/10.1016/j.jeem.2016.02.001

Rosenthal, R. (1979). The file drawer problem and tolerance for null results. *Psychological bulletin*, *86*(3), 638. https://doi.org/10.1037/0033-2909.86.3.638

Rupinski, M. T., & Dunlap, W. P. (1996). Approximating Pearson product-moment correlations from Kendall's tau and Spearman's rho. *Educational and psychological measurement*, *56*(3), 419-429. https://doi.org/10.1177/0013164496056003004

Russell, J. A. (1980). A circumplex model of affect. *Journal of personality and social psychology, 39*(6), 1161. https://psycnet.apa.org/doi/10.1037/h0077714

Russell, J. A. (1991). Culture and the categorization of emotions. *Psychological bulletin*, *110*(3), 426. https://psycnet.apa.org/doi/10.1037/0033-2909.110.3.426

Sahebkar, A. (2013a). Does PPARγ2 gene Pro12Ala polymorphism affect nonalcoholic fatty liver disease risk? Evidence from a meta-analysis. *DNA and cell biology*, *32*(4), 188-198. https://doi.org/10.1089/dna.2012.1947

Sahebkar, A. (2013b). Why it is necessary to translate curcumin into clinical practice for the prevention and treatment of metabolic syndrome?. *Biofactors*, *39*(2), 197-208. https://doi.org/10.1002/biof.1062

Satorra, A., & Bentler, P. M. (2001). A scaled difference chi-square test statistic for moment structure analysis. *Psychometrika*, *66*(4), 507-514. https://doi.org/10.1007/BF02296192

Schermelleh-Engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures. *Methods of psychological research online*, *8*(2), 23-74.

Schneider, C. R., Zaval, L., Weber, E. U., & Markowitz, E. M. (2017). The influence of anticipated pride and guilt on pro-environmental decision making. *PloS one*, *12*(11), e0188781. https://doi.org/10.1371/journal.pone.0188781

Schoemann, A. M., Boulton, A. J., & Short, S. D. (2017). Determining power and sample size for simple and complex mediation models. *Social Psychological and Personality Science, 8*(4), 379-386. https://doi.org/10.1177/1948550617715068

Schraudner, M. Schraudner, M., Schroth, F., Jütting, M. Kaiser, S., Millard, J., van der Graaf, S. (2018, November 6th-7th). *Social Innovation. The Potential for Technology Development, RTOs and Industry.* The RTO Innovation Summit 2018, Brussels, Belgium.

Schuitema, G., & Bergstad, C. J. (2018). Acceptability of environmental policies. In L. Steg, & J. I. M. de Groot (Eds.), *Environmental psychology: An introduction* (pp. 295-306). Wiley. https://doi.org/10.1002/9781119241072.ch29

Schulte, E., Scheller, F., Sloot, D., & Bruckner, T. (2022). A meta-analysis of residential PV adoption: the important role of perceived benefits, intentions and antecedents in solar energy acceptance. *Energy Research & Social Science*, *84*, 102339. https://doi.org/10.1016/j.erss.2021.102339

Schultz, P. W. (2001). The structure of environmental concern: Concern for self, other people, and the biosphere. *Journal of environmental psychology*, *21*(4), 327-339. https://doi.org/10.1006/jevp.2001.0227

Schultz, P. W. (2022). Secret agents of influence: Leveraging social norms for good. *Current Directions in Psychological Science, 31*(5), 443–450. https://doi.org/10.1177/09637214221109572

Schultz, W. P., Khazian, A. M., & Zaleski, A. C. (2008). Using normative social influence to promote conservation among hotel guests. *Social influence, 3*(1), 4-23. https://doi.org/10.1080/15534510701755614

Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J., & Griskevicius, V. (2007). The constructive, destructive, and reconstructive power of social norms. *Psychological science*, *18*(5), 429-434. https://doi.org/10.1111/j.1467-9280.2007.01917.x

Schumann, D. (2015). Public acceptance. In W. Kuckshinrichs, & J. F. Hake (Eds.), *Carbon Capture, storage and us*e (pp. 221–251). Springer. https://doi.org/10.1007/978-3-319-11943-4_11

Schwartz, S. H. (1968). Words, deeds and the perception of consequences and responsibility in action situations. *Journal of personality and social psychology*, *10*(3), 232-242. https://psycnet.apa.org/doi/10.1037/h0026569

Schwartz, S. H. (1977). Normative influences on altruism. *Advances in experimental social psychology 10*, 221-279. https://doi.org/10.1016/S0065-2601(08)60358-5

Scovell, M. D. (2022). Explaining hydrogen energy technology acceptance: A critical review. *International Journal of Hydrogen Energy*, *47*(19), 10441-10459. https://doi.org/10.1016/j.ijhydene.2022.01.099

Scovell, M., McCrea, R., Walton, A., & Poruschi, L. (2024). Local acceptance of solar farms: The impact of energy narratives. *Renewable and Sustainable Energy Reviews*, *189*, 114029. https://doi.org/10.1016/j.rser.2023.114029

Seyfang, G., & Haxeltine, A. (2012). Growing grassroots innovations: exploring the role of community-based initiatives in governing sustainable energy transitions. *Environment and Planning C: Government and Policy*, *30*(3), 381-400. https://doi.org/10.1068/c10222

Shackley, S., McLachlan, C., & Gough, C. (2004). The public perception of carbon dioxide capture and storage in the UK: results from focus groups and a survey. *Climate Policy*, *4*(4), 377-398. https://doi.org/10.1080/14693062.2004.9685532

Shaheen, S. A., Martin, E., & Lipman, T. E. (2008). Dynamics in behavioral response to fuel-cell vehicle fleet and hydrogen fueling infrastructure: an exploratory study. *Transportation research record*, *2058*(1), 155-162. https://doi.org/10.3141/2058-19

Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika*, *52*(3-4), 591-611. https://doi.org/10.1093/biomet/52.3-4.591

Sonnberger, M., & Ruddat, M. (2017). Local and socio-political acceptance of wind farms in Germany. *Technology in Society*, *51*, 56-65. https://doi.org/10.1016/j.techsoc.2017.07.005

Sovacool, B. K. (2014a). Diversity: Energy studies need social science. Nature, *511*(7511), 529-530. https://doi.org/10.1038/511529a

Sovacool, B. K. (2014b). What are we doing here? Analyzing fifteen years of energy scholarship and proposing a social science research agenda. *Energy Research & Social Science*, *1*, 1-29. https://doi.org/10.1016/j.erss.2014.02.003

Sovacool, B. K., Axsen, J., & Sorrell, S. (2018). Promoting novelty, rigor, and style in energy social science: Towards codes of practice for appropriate methods and research design. *Energy research & social science*, *45*, 12-42. https://doi.org/10.1016/j.erss.2018.07.007

Sovacool, B. K., Baum, C. M., & Low, S. (2022a). Climate protection or privilege? A whole systems justice milieu of twenty negative emissions and solar geoengineering technologies. *Political Geography*, *97*, 102702. https://doi.org/10.1016/j.polgeo.2022.102702

Sovacool, B. K., Baum, C. M., & Low, S. (2022b). Determining our climate policy future: expert opinions about negative emissions and solar radiation management pathways. *Mitigation and adaptation strategies for global change*, *27*(8), 58. https://doi.org/10.1007/s11027-022-10030-9

Sovacool, B. K., Heffron, R. J., McCauley, D., & Goldthau, A. (2016). Energy decisions reframed as justice and ethical concerns. *Nature Energy*, *1*(5), 1-6. https://doi.org/10.1038/nenergy.2016.24

Sovacool, B. K., Newell, P., Carley, S., & Fanzo, J. (2022). Equity, technological innovation and sustainable behaviour in a low-carbon future. *Nature human behaviour*, *6*(3), 326-337. https://doi.org/10.1038/s41562-021-01257-8

Sovacool, B. K., Ryan, S. E., Stern, P. C., Janda, K., Rochlin, G., Spreng, D., ... & Lutzenhiser, L. (2015). Integrating social science in energy research. *Energy Research & Social Science*, *6*, 95-99. https://doi.org/10.1016/j.erss.2014.12.005

Stavraki M., Lamprinakos G., Briñol P., Petty R. E., Karantinou K., Díaz D. (2021). The influence of emotions on information processing and persuasion: A differential appraisals perspective. *Journal of Experimental Social Psychology*, *93*, 104085. https://doi.org/10.1016/j.jesp.2020.104085

Steg, L., Bolderdijk, J. W., Keizer, K., & Perlaviciute, G. (2014). An integrated framework for encouraging pro-environmental behaviour: The role of values, situational factors and goals. *Journal of Environmental psychology*, *38*, 104-115. https://doi.org/10.1016/j.jenvp.2014.01.002

Steg, L., & De Groot, J. (2010). Explaining prosocial intentions: Testing causal relationships in the norm activation model. *British journal of social psychology*, *49*(4), 725-743. https://doi.org/10.1348/014466609X477745

Steg, L., Perlaviciute, G., Sovacool, B. K., Bonaiuto, M., Diekmann, A., Filippini, M., ... & Woerdman, E. (2021). A research agenda to better understand the human dimensions of energy transitions. *Frontiers in psychology*, *12*, 672776. https://doi.org/10.3389/fpsyg.2021.672776

Steg, L., Perlaviciute, G., & Van der Werff, E. (2015). Understanding the human dimensions of a sustainable energy transition. *Frontiers in psychology*, *6*, 805. https://doi.org/10.3389/fpsyg.2015.00805

Steg, L., & Vlek, C. (2009). Encouraging pro-environmental behaviour: An integrative review and research agenda. *Journal of environmental psychology*, *29*(3), 309-317. https://doi.org/10.1016/j.jenvp.2008.10.004

Stern, P. C., Dietz, T., Abel, T., Guagnano, G. A., & Kalof, L. (1999). A value-belief-norm theory of support for social movements: The case of environmentalism. *Human ecology review*, 81-97.

Suhay, E. (2015). Explaining group influence: The role of identity and emotion in political conformity and polarization. *Political Behavior*, *37*(1), 221–251. https://doi.org/10.1007/s11109-014-9269-1

Taylor, S. E. (1991). Asymmetrical effects of positive and negative events: the mobilization-minimization hypothesis. *Psychological bulletin*, *110*(1), 67.

Terry, D. J., & Hogg, M. A. (1996). Group norms and the attitude-behavior relationship: A role for group identification. *Personality and social psychology bulletin*, *22*(8), 776-793. https://doi.org/10.1177/0146167296228002

Terwel, B. W., Harinck, F., Ellemers, N., & Daamen, D. D. L. (2009). Competence-based and integrity-based trust as predictors of acceptance of carbon dioxide capture and storage (CCS). *Risk Analysis: An International Journal*, *29*(8), 1129-1140. https://doi.org/10.1111/j.1539-6924.2009.01256.x

te Velde, V. L., & Louis, W. (2022). Conformity to descriptive norms. *Journal of Economic Behavior & Organization*, *200*, 204–222. https://doi.org/10.1016/j.jebo.2022.05.017

Thøgersen, J. (2006). Norms for environmentally responsible behaviour: An extended taxonomy. *Journal of Environmental Psychology*, *26*(4), 247–261. https://doi.org/10.1016/j.jenvp.2006.09.004

Thomas, E. F., & McGarty, C. A. (2009). The role of efficacy and moral outrage norms in creating the potential for international development activism through group-based interaction. *British Journal of Social Psychology*, *48*(1), 115-134. https://doi.org/10.1348/014466608X313774

Toft, M. B., Schuitema, G., & Thøgersen, J. (2014). Responsible technology acceptance: Model development and application to consumer acceptance of Smart Grid technology. *Applied Energy*, *134*, 392-400. https://doi.org/10.1016/j.apenergy.2014.08.048

Tong E. M. W. (2015). Differentiation of 13 positive emotions by appraisals. *Cognition and Emotion*, *29*(3), 484–503. https://doi.org/10.1080/02699931.2014.922056

United Nations (UN) (2015). Transforming Our World: the 2030 Agenda for Sustainable Development. Resolution adopted by the General Assembly on 25 September 2015, A/RES/70/1. UN General Assembly: New York.

van der Horst, D., Grant, R., Montero, A. M., & Garneviciene, A. (2021). Energy justice and social acceptance of renewable energy projects in the Global South. In S. Batel, & D. Rudolph (Eds.), *A critical approach to the social acceptance of renewable energy infrastructures: Going beyond green growth and sustainability* (pp. 217-234). Springer.

Van der Werff, E., & Steg, L. (2016). The psychology of participation and interest in smart energy systems: Comparing the value-belief-norm theory and the value-identity-personal norm model. *Energy research & social science*, *22*, 107-114. https://doi.org/10.1016/j.erss.2016.08.022

Van der Werff, E., Steg, L., & Keizer, K. (2013). It is a moral issue: The relationship between environmental self-identity, obligation-based intrinsic motivation and pro-environmental behaviour. *Global environmental change*, *23*(5), 1258-1265. https://doi.org/10.1016/j.gloenvcha.2013.07.018

Van Kleef, G. A., & Fischer, A. H. (2016). Emotional collectives: How groups shape emotions and emotions shape groups. *Cognition and Emotion*, *30*(1), 3-19. https://doi.org/10.1080/02699931.2015.1081349

Van't Veer, A. E., & Giner-Sorolla, R. (2016). Pre-registration in social psychology—A discussion and suggested template. *Journal of experimental social psychology*, *67*, 2-12. https://doi.org/10.1016/j.jesp.2016.03.004

Van Valkengoed, A. M., Perlaviciute, G., & Steg, L. (2024). From believing in climate change to adapting to climate change: The role of risk perception and efficacy beliefs. *Risk Analysis*, *44*(3), 553-565. https://doi.org/10.1111/risa.14193

Van Valkengoed, A. M., & Steg, L. (2019). Meta-analyses of factors motivating climate change adaptation behaviour. *Nature climate change*, *9*(2), 158-163. https://doi.org/10.1038/s41558-018-0371-y

Vargha, A., & Delaney, H. D. (1998). The Kruskal-Wallis test and stochastic homogeneity. *Journal of Educational and behavioral Statistics*, *23*(2), 170-192. https://doi.org/10.3102/10769986023002170

Verplanken, B. (1989). Beliefs, attitudes, and intentions toward nuclear energy before and after Chernobyl in a longitudinal within-subjects design. *Environment and Behavior, 21*(4), 371-392. https://doi.org/10.1177/0013916589214001

Verbruggen, A., Fischedick, M., Moomaw, W., Weir, T., Nadaï, A., Nilsson, L. J., ... & Sathaye, J. (2010). Renewable energy costs, potentials, barriers: Conceptual issues. *Energy policy*, *38*(2), 850-861. https://doi.org/10.1016/j.enpol.2009.10.036

Vesely, S., Klöckner, C. A., Carrus, G., Chokrai, P., Fritsche, I., Masson, T., ... & Udall, A. M. (2022). Donations to renewable energy projects: The role of social norms and donor anonymity. *Ecological Economics*, *193*, 107277. https://doi.org/10.1016/j.ecolecon.2021.107277

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of statistical software*, *36*(3), 1-48. https://doi.org/10.18637/jss.v036.i03

Viechtbauer, W., & Cheung, M. W. L. (2010). Outlier and influence diagnostics for meta-analysis. *Research synthesis methods*, *1*(2), 112-125. https://doi.org/10.1002/jrsm.11

Vining A., & Merrick M. (2012). Environmental epiphanies: Theoretical foundations and practical applications. In S.D. Clayton (Ed.), *The Oxford handbook of environmental and conservation psychology* (pp. 485-508). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199733026.013.0026

Visschers, V. H., & Siegrist, M. (2014). Find the differences and the similarities: Relating perceived benefits, perceived costs and protected values to acceptance of five energy technologies. *Journal of Environmental Psychology*, *40*, 117-130. https://doi.org/10.1016/j.jenvp.2014.05.007

Walker, D. A. (2003). JMASM9: converting Kendall's tau for correlational or meta-analytic analyses. *Journal of Modern Applied Statistical Methods*, *2*, 525-530. https://doi.org/10.1037/0021-9010.90.1.175

Walker, G., & Devine-Wright, P. (2008). Community renewable energy: What should it mean?. *Energy policy*, *36*(2), 497-500. https://doi.org/10.1016/j.enpol.2007.10.019

Wang, X., & Zhang, C. (2020). Contingent effects of social norms on tourists' pro-environmental behaviours: The role of Chinese traditionality. *Journal of Sustainable Tourism*, *28*(10), 1646-1664. https://doi.org/10.1080/09669582.2020.1746795

Warren, D. C., Carley, S. R., Krause, R. M., Rupp, J. A., & Graham, J. D. (2014). Predictors of attitudes toward carbon capture and storage using data on world views and CCS-specific attitudes. *Science and Public Policy*, *41*(6), 821-834. https://doi.org/10.1093/scipol/scu016

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales. *Journal of personality and social psychology*, *54*(6), 1063. https://psycnet.apa.org/doi/10.1037/0022-3514.54.6.1063

Whitmarsh, L., Xenias, D., & Jones, C. R. (2019). Framing effects on public support for carbon capture and storage. *Palgrave Communications*, *5*(1). https://doi.org/10.1057/s41599-019-0217-x

Wolsink, M. (2007). Wind power implementation: the nature of public attitudes: equity and fairness instead of 'backyard motives'. *Renewable and sustainable energy reviews*, *11*(6), 1188-1207. https://doi.org/10.1016/j.rser.2005.10.005

Wolsink, M. (2012). The research agenda on social acceptance of distributed generation in smart grids: Renewable as common pool resources. *Renewable and Sustainable Energy Reviews*, *16*(1), 822–835. https://doi.org/10.1016/j.rser.2011.09.006

Wolske, K. S., Gillingham, K. T., & Schultz, P. W. (2020). Peer influence on household energy behaviours. *Nature Energy*, *5*(3), 202-212. https://doi.org/10.1038/s41560-019-0541-9

Wolske, K. S., Stern, P. C., & Dietz, T. (2017). Explaining interest in adopting residential solar photovoltaic systems in the United States: Toward an integration of behavioral theories. *Energy research & social science*, *25*, 134-151. https://doi.org/10.1016/j.erss.2016.12.023

Wonneberger, A. (2018). Environmentalism—a question of guilt? Testing a model of guilt arousal and effects for environmental campaigns. *Journal of Nonprofit & Public Sector Marketing*, *30*(2), 168–186. https://doi.org/10.1080/10495142.2017.1326873

Wood, J. V. (1989). Theory and research concerning social comparisons of personal attributes. *Psychological bulletin*, *106*(2), 231. https://psycnet.apa.org/doi/10.1037/0033-2909.106.2.231

Wüstenhagen, R., Wolsink, M., & Bürer, M. J. (2007). Social acceptance of renewable energy innovation: An introduction to the concept. *Energy Policy*, *35*(5), 2683–2691. https://doi.org/10.1016/j.enpol.2006.12.001

Yazdanpanah, M., Komendantova, N., & Ardestani, R. S. (2015). Governance of energy transition in Iran: Investigating public acceptance and willingness to use renewable energy sources through socio-psychological model. *Renewable and Sustainable Energy Reviews*, *45*, 565-573. https://doi.org/10.1016/j.rser.2015.02.002

Yun, S., & Lee, J. (2015). Advancing societal readiness toward renewable energy system adoption with a socio-technical perspective. *Technological Forecasting and Social Change*, *95*, 170-181. https://doi.org/10.1016/j.techfore.2015.01.016

Zhou, S., Matisoff, D. C., Kingsley, G. A., & Brown, M. A. (2019). Understanding renewable energy policy adoption and evolution in Europe: The impact of coercion, normative emulation, competition, and learning. *Energy Research & Social Science*, *51*, 1-11. https://doi.org/10.1016/j.erss.2018.12.011

Zwicker, M. V., Nohlen, H. U., Dalege, J., Gruter, G. J. M., & van Harreveld, F. (2020). Applying an attitude network approach to consumer behaviour towards plastic. *Journal of Environmental Psychology*, *69*, 101433. https://doi.org/10.1016/j.jenvp.2020.101433

LIST OF APPENDICES

APPENDIX A (Study 1)

Table 1A - *Variable's codification*

Original Variable Name	**Merged/modified Variable Name**

Age	Age
Attitude, Attitudes, Attitude to renewable energy, Acceptance, General Attitude, Environmental attitude, Consumer Attitude, Attitude toward rooftop PV installation, Attitude construct, Acceptance of complete RES transition, General attitudes toward the use of woody biomass to produce energy, Support for solar, Attitude change toward renewable energy source, Support for utility-scale solar construction in the U.S. for the National, Support for utility-scale solar construction in one's own county for the National, Support for utility-scale solar construction in the U.S. for the Southwest, Support for utility-scale solar construction in one's own county for the Southwest, Support for a CCS facility in Indiana, Support for CCS Facilities "Somewhere" in the United States, Support for CCS Facilities Near Respondents' Homes or Communities, Predict a NIMBY Reaction, CE Acceptance, Support of government policies encouraging renewable energy development, Storing carbon dioxide underground is a good approach to protecting the environment, Preference for wind power, Preference for solar energy, Preference for biomass energy, Support for renewable energy technologies, Community acceptance of large-scale solar energy installations, Attitude towards renewable energy, Acceptance of a BGP development in respondents' vicinity, Support through opposition for Solid Carbon, CSS support, Preference for energy supply from solar power, Individual-level CCS support, Wind Farm Support, Attitude toward the Barendrecht CCS plan, Acceptance of the project, Support for funding	Acceptability
Environmental Concern, Perceived susceptibility, Problem perception, Concern, Attitude toward environmental protection	Climate Change Concern
Political positioning, Political Orientation, Political Ideology, Democrats	Conservative
Consumer Innovativeness, Openness to experience, Consumer Novelty Seeking, Openness to Change, Innovativeness	Consumer Innovativeness
Ecological Lifestyle, Ecological Behaviour, Environmental Behaviour	Ecological Lifestyle
Education, Academic level	Education
Perceived Environmental Responsibility, Moral Norms, Perceived accountability for the environmental motives, Green Norm, Environmental Value, Personal Norm, Subjective Norms, Subjective norms of sustainable behaviours	Environmental Responsibility
Fairness, Perceived fairness of decision-making process, Consultation process with wind project development, Perceived procedural justice, Fairness ET, CSS fairness & transparency of decision-making process, Perceived process as fair, Process fairness	Fairness
Gender, Sex, Female, Male	Gender
Government initiatives, Government initiatives, Perceived government policy	Government Initiatives
Income, Socioeconomic level	Income
Intention, Willingness to pay, Tendency to adopt photovoltaic systems, Adoption of a renewable RHS, Willingness to pay more for renewable electricity, Having solar, Willingness to pay for energy from renewable sources, Intention to adopt rooftop solar panels at home, Intention to use biodiesel, Planning outcome of wind turbine applications, Adoption of soil organic carbon sequestration, Adoption of solar technology, Biogas energy adoption, Considering a solar installation, Willing to Make an Environmental Effort to Promote Biogas, Public acceptance, Willingness to participate in CSS programs, Intention to purchase solar panel, Intention to use renewable energy, Behaviour intention, Behavioral intention, Anti-incinerator sentiment, Intention to adopt, Adoption, Intention of rooftop PV installation, Intention to utilize RPT, Purchase Intention, Consumers' intention, Buying intention of solar energy technologies, Adoption and diffusion of SET, Desire to adopt green energy technologies, Usage Intention, Willingness to utilize solar energy,Customers purchase intention, Interest in Talking to an RPV Installer, Purchase intention, Customer intention for the adoption of photovoltaic Panel system, Biofuel intention	Acceptance
Moral norm, Moral norms, Personal norms	Personal Norm

Negative emotional response, Negative affect, Negative emotion, Negative emotions	Negative Emotional Response
Perceived behavioural control, Incompatibility with their house, Financial abilities, Perception about self-effectiveness, Unsuitable home, Self-efficacy, Self-efficacy beliefs	Perceived Behavioral Control
Perceived benefits, Potential benefits to the local economy, Environmental improvements, Relative advantages, Perceived usefulness, Perceived environmental relative advantages, Green energy technology benefits, Belief of solar energy benefits, Personal Benefits, Product benefit, Advantage, Perceived Economic Returns, Beliefs about the benefits of Solar Energy	Perceived Benefits
Perceived Cost, Initial costs of installing solar panels, Cost of green energy technology, Perceived'SET's price, Green energy technology costs, Adoption Cost, Cost of solar energy, Beliefs about the cost of RE utilization, Cost, Expense Concerns, Perceived cost maintenance, Economic	Perceived Cost
Perceived ease of use, Perceived SET's ease of use, Effort Expectancy beliefs, Ease to use	Perceived Ease of Use
Perceived risk, Impact of the project on your living standard, Potential impact on welfare, Perceived risks, Risk perception, Technology Barriers, Perceived barriers	Perceived Risks
Uncertainty in regard to the performance of solar panels, Development level of renewable energy, Perceived SET's reliability, Outcome efficacy, System quality, Perceived system quality	Perceived Technology Reliability
Responsibility, Control over nature, Beliefs about anthropogenic causation of climate change, Ascription of responsibility	Perception of Human Impact on Climate Change
Place attachment, Place identity, Place attachment/identity	Place Attachment
Positive emotional response, Positive affect, Affect, General affect	Positive Emotional Response
Subjective Knowledge, CCS knowledge, Self-perceived knowledge, Familiarity with geoengineering, Perceived knowledge of CCS technology, Information, Public cognition, Perceived degree of information	Subjective Knowledge
Subjective Norm, Subjective norms, Social Influence, Descriptive norm, Subjective norms of sustainable behaviour, Perception about neighbor participation, Perception of neighbors' participation, Observability, Injunctive norms, Social factors	Social Norms
Trust in decision-makers, Public trust, Perceived Trust, Trust, Social trust, Trust in PV Industry	Trust in Decision Makers

APPENDIX B (Study 2)

Mitigation scenario

Mitigation energy technologies represent a crucial area in the fight against climate change. These technologies are designed to reduce greenhouse gas emissions and mitigate the impact of human activities on the environment. Among the most important technologies are renewable energy sources, such as solar energy that captures the sun's energy through *photovoltaic panels, wind energy that harnesses the power of the wind through turbines, hydropower that harnesses the flow of water to generate electricity, or geothermal energy that harnesses heat from the earth's subsurface to produce power. These sources can progressively replace traditional fossil fuel-based energy sources, drastically reducing emissions of carbon dioxide and other greenhouse gases. Mitigation energy technologies aim to reduce climate change, conserve natural resources and create a greener and more sustainable energy base for future generations. These technologies, some already widely adopted and others still in the experimental stage, are one of the main interventions in the fight against climate change.*

Adaptation scenario

Adaptation energy technologies involve large-scale interventions in the Earth system to offset the effects of global warming. One of the main proposals is climate engineering (or geoengineering), which includes techniques such as solar radiation management, ocean fertilization, or so-called "cloud engineering". Solar radiation management involves reflecting some of the sunlight back into space, thereby reducing the solar energy reaching Earth and helping to cool the planet. Ocean fertilization involves adding nutrients to the seas to increase phytoplankton growth, a process that would help capture atmospheric carbon. Finally, "cloud engineering" involves modifying clouds to increase their reflectivity and thus reduce Earth's temperature. The main goal of adaptation energy technologies is to directly influence the climate system by trying to offset the negative effects of climate change. These technologies are in the experimental stage, representing an evolving research frontier in the fight against climate change.

Constructs' scales and items

Social Norms

1. Most people important to me would approve if I adopted these technologies to counter climate change.
2. Most people important to me would approve if I socially and politically supported these technologies to counter climate change.
3. Most people important to me would approve if I accepted a tax increase to ensure the adoption of these technologies to counter climate change.
4. Most people important to me adopt/would adopt these technologies to counter climate change.
5. Most people important to me support/would support these technologies socially and politically to counter climate change.
6. Most people important to me accept/would accept a tax increase to ensure the adoption of these technologies to counter climate change.

Personal Norm

1. I feel morally obliged to use/purchase/support such technologies, regardless of what others do.
2. I feel guilty if I do not use/purchase/support such technologies.
3. I feel good about myself when I use/purchase/support such technologies.

Positive Affective Response

Thinking about the technologies previously presented, and their potential benefits and risks, makes me feel:

1. Enthusiastic
2. Alert
3. Inspired
4. Determined
5. Excited
6. Happy
7. Surprised

Acceptability

I think such energy technologies are:

1. Valuable
2. Useful
3. Good

Technology Acceptability

I believe such energy technologies are:

1. Unnecessary – Necessary
2. Pleasant – Disturbing (R)

3. Traditional – Modern
4. Repellent – Attractive
5. Positive – Negative (R)
6. Dirty – Clean
7. Effective – Ineffective (R)
8. Morally wrong – Morally right
9. Safe – Unsafe (R)
10. Beneficial – Harmful (R)
11. Unnatural – Natural
12. Unacceptable – Acceptable

Support Intention

If there were a discussion regarding the use of such energy technologies, how likely would you be to take the following actions in favor of them?

1. Sign a petition
2. Make a donation
3. Write a letter (email) to a newspaper or magazine
4. Speak up at a public meeting
5. Vote in an election for a party that promotes the use of such technologies
6. Participate in a demonstration or public event
7. Share a post on social media

Intention to Use & Pay

1. I would accept a tax increase to adopt such technologies to counter climate change.

2. I want these technologies to be adopted to counter climate change, even if it leads to a tax increase.
3. I plan to spend money to ensure such technologies are adopted to counter climate change.
4. I would intend to use such technologies to counter climate change.
5. I would like to use such technologies to counter climate change.
6. I would use such technologies to counter climate change.

APPENDIX C (Study 3)

Mitigation SETs scenarios (Study 3a)

In this study, you will be presented with brief descriptions of different types of sustainable energy technologies. Each will describe how much energy the technology can produce in megawatts per hour (MWh). For comparison, the average annual electricity consumption of a *household in California is roughly 6 MWh. For each of these energy sources, some pros and cons will then be listed.*

After reading each description, you will be asked to answer some questions.

Solar Energy:

Solar energy harnesses sunlight to generate electricity using panels. Photovoltaic panels convert sunlight directly into electricity, and they are commonly installed on rooftops or in open fields for residential or commercial use. A single solar panel can produce around 0.005 MWh of electricity per year, while a large solar plant, consisting of multiple panels, can typically generate several thousand MWh annually.

PROS	***CONS***
• ***Clean and Sustainable****: Reduces greenhouse gases, air pollution* • ***Low Operating Costs****: Free sunlight, minimal maintenance expenses* • ***Energy Independence****: Less reliance on fossil fuels*	• ***Intermittent Availability****: Depends on sunlight, weather dependency* • ***High Initial Costs****: Expensive installation, upfront investment required* • ***Space Utilization and Impact****: Space requirements, potential ecosystem disruption*

Wind Energy:

Wind energy generates electricity by moving turbines. Wind turbines convert wind power directly into electricity, and they are commonly installed in open fields or coastal areas with strong winds, as well as offshore in bodies of water such as the ocean. A single wind turbine can produce around 8 MWh of electricity per year, while a large wind farm, consisting of multiple turbines, can typically generate several million MWh annually.

PROS	***CONS***
• ***Renewable and Abundant****: Endless wind, no fuel depletion* • ***Low Operating Costs****: Free wind, minimal maintenance expenses* • ***Land Multifunctionality****: Shared land use, agricultural compatibility*	• ***Intermittent Availability****: Variable wind speeds, weather dependency* • ***High Initial Costs****: Expensive installation, upfront investment required* • ***Visual, Noise, and wildlife Impact****: Visual pollution, noise disturbance, possible danger to birds*

Biofuels:

Biofuels produce energy from organic materials, such as plants, crops, or organic waste. Biofuels use processes like fermentation, distillation, or chemical conversion to produce energy, and they can be used in transportation, heating, or electricity generation. A single gallon of advanced biofuels can produce around 0.6 MWh of energy, while a large plant can typically generate several million MWh annually.

PROS	CONS
• ***Renewable and Sustainable****: Derived from organic materials, reduce emissions* • ***Diverse Feedstock Options****: Can use various biomass sources* • ***Energy Independence****: Less reliance on fossil fuels*	• ***Land Use and Competition****: Can compete with food production, habitat loss* • ***Limited Scale and Efficiency****: Challenges in scaling up production* • ***Emissions and Environmental Impact****: Can still produce greenhouse gases*

Hydrogen Energy:

Hydrogen energy produces electricity through the use of hydrogen gas in fuel cells. Fuel cells generate electricity by combining hydrogen with oxygen releasing stored chemical energy, and it can be used in transportation, stationary power generation, or portable power sources. A single kilogram of hydrogen can produce around 1 MWh of electricity, while a large-scale application can typically generate several thousand MWh annually.

PROS	CONS
• ***Clean and Versatile****: Low emissions, multiple applications* • ***High Energy Density****: Efficient energy storage, versatile usage* • ***Renewable Potential****: Can be produced from renewable sources*	• ***Production Challenges****: Requires energy-intensive production methods* • ***Storage and Distribution****: Complex infrastructure, safety concerns* • ***Partial reliance on fossil fuels****: large-scale hydrogen production could be linked to fossil fuels*

Tidal Energy:

Tidal energy generates electricity by moving turbines. Tidal turbines convert the kinetic energy of rising and falling ocean tides directly into electricity, and they are commonly installed in coastal regions with significant and predictable tidal ranges. A single tidal turbine can produce around 6000 MWh of electricity per year, while a large tidal plant, consisting of multiple turbines, can typically generate tens of thousand MWh annually.

PROS	*CONS*
• ***Predictable and Reliable****: Consistent tidal patterns, reliable energy generation* • ***Renewable and Low Impact****: No greenhouse gas emissions* • ***High Energy Density****: Tidal currents carry significant energy*	• ***High Initial Costs****: Expensive installation and maintenance, upfront investment required* • ***Geographical Constraints****: Suitable sites restricted to specific coastal areas* • ***Ecosystem Disruption****: Potential harm to marine life habitats*

Hydroelectric Energy:

Hydroelectric energy generates electricity by moving turbines. Hydroelectric turbines convert the gravitational force of falling or flowing water directly into energy, and they are commonly installed in mountainous regions with ample water resources. Small hydroelectric installations, such as from a river, can produce around 3000 MWh of electricity per year, while large hydroelectric dams can typically generate several million MWh annually.

PROS	*CONS*
• ***Predictable and Reliable****: Consistent water flow, reliable energy generation* • ***Low Operating Costs****: Free flowing water, minimal maintenance expenses* • ***Versatile Application****: Suitable for various scales, from small to large projects*	• ***High Initial Costs****: Expensive installation and maintenance, upfront investment required* • ***Geographical Constraints****: Dependent on suitable water resources and terrain* • ***Ecosystem Disruption****: Potential harm to aquatic habitats*

Constructs' scales and items (Study 3a)

Subjective Knowledge

Thinking about XX energy I feel:

1. Unfamiliar – Familiar
2. Knowledgeable – Unknowledgeable (R)

Feasibility

I think that adopting XX energy is:

1. Feasible - Unfeasible (R)
2. Impossible - Possible
3. Difficult - Easy
4. Practicable - Impracticable (R)

Support Intention

Considering the following behaviors regarding XX energy, I am willing to:

1. Invest in public funds that support its development and implementation
2. Seek information about it, its benefits, and its risks
3. Share information about it with others (e.g., through social media)
4. Donate money to encourage its research and development
5. Vote for a political candidate because of their support for developing this technology
6. Pay more on my utility bill to have the energy in my home come from this technology
7. Sign a petition promoting its use
8. Participate in a public event promoting it

Note:

1) When XX is reported in the questionnaire, this should be replaced with the name of the specific mitigation technology presented.

Mitigation SETs scenarios (Study 3b)

In this study, you will be presented with a brief description of an energy technology.

This description will include the amount of energy the technology can produce in megawatts per hour (MWh). For comparison, a household's average electricity consumption in California is about 6 MWh per year.

The description will also include a list of pros and cons associated with the technology.

After reading the description, you will be asked to answer some questions.

Solar Energy:

Solar energy harnesses sunlight to generate electricity using panels. Photovoltaic panels convert sunlight directly into electricity, and they are commonly installed on rooftops or in open fields for residential or commercial use. A single solar panel can produce around 0.005 MWh of electricity per year, while a large solar plant, consisting of multiple panels, can typically generate several thousand MWh annually.

PROS	***CONS***
• ***Clean and Sustainable****: Reduces greenhouse gases, air pollution* • ***Low Operating Costs****: Free sunlight, minimal maintenance expenses* • ***Energy Independence****: Less reliance on fossil fuels*	• ***Intermittent Availability****: Depends on sunlight, weather dependency* • ***High Initial Costs****: Expensive installation, upfront investment required* • ***Space Utilization and Impact****: Space requirements, potential ecosystem disruption*

Hydrogen Energy:

Hydrogen energy produces electricity through the use of hydrogen gas in fuel cells. Fuel cells generate electricity by combining hydrogen with oxygen releasing stored chemical energy, and it can be used in transportation, stationary power generation, or portable power sources.

A single kilogram of hydrogen can produce around 1 MWh of electricity, while a large-scale applications can typically generate several thousand MWh annually.

PROS	***CONS***
• ***Clean and Versatile****: Low emissions, multiple applications* • ***High Energy Density****: Efficient energy storage, versatile usage* • ***Renewable Potential****: Can be produced from renewable sources*	• ***Production Challenges****: Requires energy-intensive production methods* • ***Storage and Distribution****: Complex infrastructure, safety concerns* • ***Partial reliance on fossil fuels****: large-scale hydrogen production could be linked to fossil fuels*

Constructs' scales and items (Study 3b)

Baseline Support Intention

Considering the following behaviors regarding XX energy, I am willing to:

1. Invest in public funds that support its development and implementation
2. Seek information about it, its benefits, and its risks
3. Share information about it with others (e.g., through social media)
4. Donate money to encourage its research and development
5. Vote for a political candidate because of their support for developing this technology
6. Pay more on my utility bill to have the energy in my home come from this technology
7. Sign a petition promoting its use
8. Participate in a public event promoting it

Positive Affect

Condition 1:

Now, knowing that you are more/less willing to support XX energy than the average Californian, to what extent do you feel each of the following on a scale from 1 “very slightly or not at all” to 5 “extremely”?

Condition 2:

Now, knowing your XX energy support score, to what extent do you feel each of the following on a scale from 1 “very slightly or not at all” to 5 “extremely”?

1. interested
2. excited
3. strong
4. enthusiastic
5. proud
6. inspired
7. determined
8. attentive
9. active
10. alert

Negative Affect

Condition 1:

Now, knowing that you are more/less willing to support XX energy than the average Californian, to what extent do you feel each of the following on a scale from 1 “very slightly or not at all” to 5 “extremely”?

Condition 2:

Now, knowing your XX energy support score, to what extent do you feel each of the following on a scale from 1 “very slightly or not at all” to 5 “extremely”?

1. distressed
2. upset
3. guilty
4. scared
5. hostile
6. irritable
7. ashamed
8. nervous
9. jittery
10. afraid

Surprise

Condition 1:

Now, knowing that you are more/less willing to support XX energy than the average Californian, to what extent do you feel surprised on a scale from 1 “very slightly or not at all” to 5 “extremely”?

Condition 2:

Now, knowing your XX energy support score, to what extent do you feel surprised on a scale from 1 “very slightly or not at all” to 5 “extremely”?

Contentment

Condition 1:

Now, knowing that you are more/less willing to support XX energy than the average Californian, to what extent do you feel contented on a scale from 1 “very slightly or not at all” to 5 “extremely”?

Condition 2:

Now, knowing your XX energy support score, to what extent do you feel contented on a scale from 1 “very slightly or not at all” to 5 “extremely”?

Follow-up Support Intention

Considering the same behaviors regarding XX energy you thought about earlier, I am willing to:

1. Invest in public funds that support its development and implementation
2. Seek information about it, its benefits, and its risks
3. Share information about it with others (e.g., through social media)

4. Donate money to encourage its research and development
5. Vote for a political candidate because of their support for developing this technology
6. Pay more on my utility bill to have the energy in my home come from this technology
7. Sign a petition promoting its use
8. Participate in a public event promoting it

Support Behavior

Given the relevance of XX energy in promoting an energy transition to renewable and sustainable sources, it is important to promote its awareness.

Below, you can find a series of articles about XX energy. Each article covers a different topic (shown in parentheses) related to XX energy.

You can freely choose whether or not to download the following articles. If you are interested and decide to download them, you can choose which and how many articles to download.

1. Do not download any articles
2. Article 1 (What is XX energy and why it is needed)
3. Article 2 (Risks and benefits of XX energy)
4. Article 3 (How to use XX energy)
5. Article 4 (XX energy in California)

Note:

1) When XX is reported in the questionnaire, this should be replaced with Solar or Hydrogen, depending on the technology to which participants will be assigned

2) When more/less is reported in the questionnaire, only one of the two options will be presented to participants based on their mean response to the Baseline technology support intention scale

Figure 1C – *Experimental group manipulation example (Study 3b)*

Now, think about the questions you just answered.
We recently surveyed a sample of fellow Californians and asked them the same questions about what they would be willing to do regarding Solar energy. Their average score for those questions was **5.49 (on a range from 0 to 10)**. Based on what you said you would be willing to do regarding Solar energy, we calculated your average score. **Higher scores mean you are more willing to support Solar energy, lower scores mean less willingness to support Solar energy**.
Your score is shown below:

Californian Average	Your Score
5.49	6.75

You are more willing to support Solar energy than other Californians

Figure 2C - *Control group manipulation example (Study 3b)*

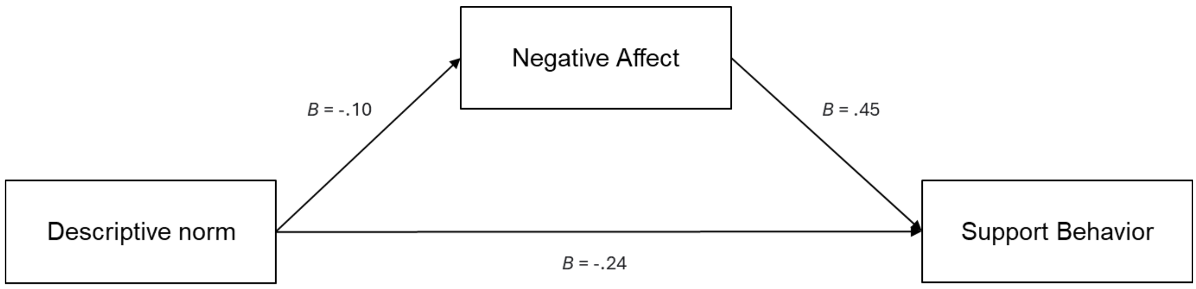
Now, think about the questions you just answered.
Based on what you said you would be willing to do regarding Hydrogen energy, we calculated your average score **(on a range from 0 to 10)**. **Higher scores mean you are more willing to support Hydrogen energy, lower scores mean less willingness to support Hydrogen energy**. Your average score is shown below:

Your Score

4.38

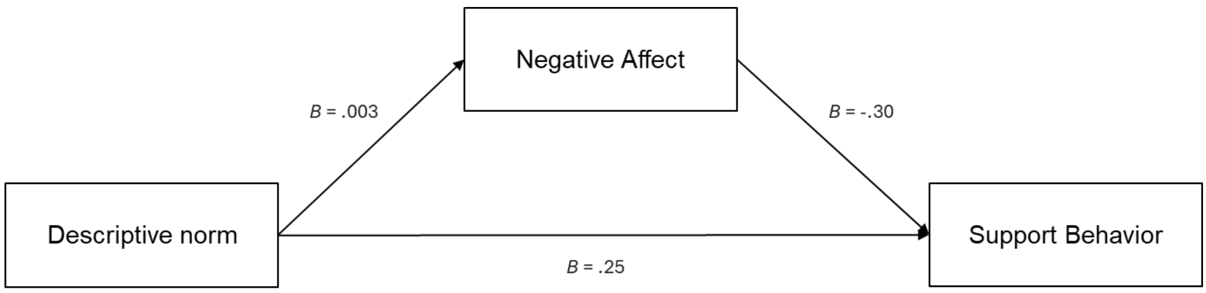
Figure 3C - *Negative Affect mediation below average (Conditional effects)*

SOLAR



Note: *Dependent variable: Support Behavior;* $R = .19$; $R^2 = .04$ ($F_{(2,135)} = 2.50$, $p = .086$)*; Indirect effect:* $B = -.04$, *BootSE = .05, BootLLCI = -.17, BootULCI = .02.*

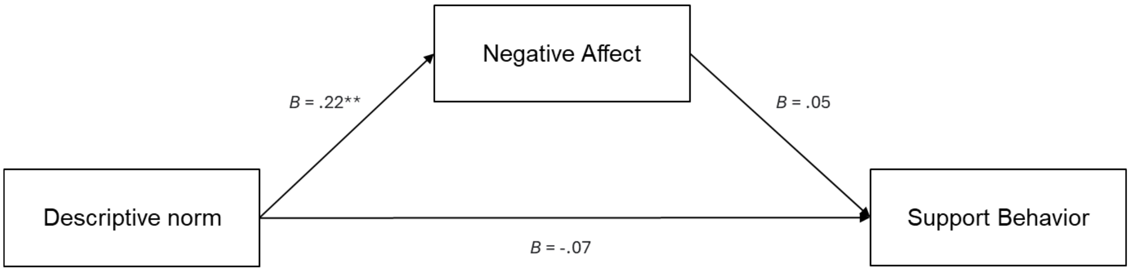
HYDROGEN



Note: *Dependent variable: Support Behavior;* $R = .12$; $R^2 = .01$ ($F_{(2,96)} = .71$, $p = .492$)*; Indirect effect:* $B = -.001$, *BootSE = .03, BootLLCI = -.03, BootULCI = .07.*

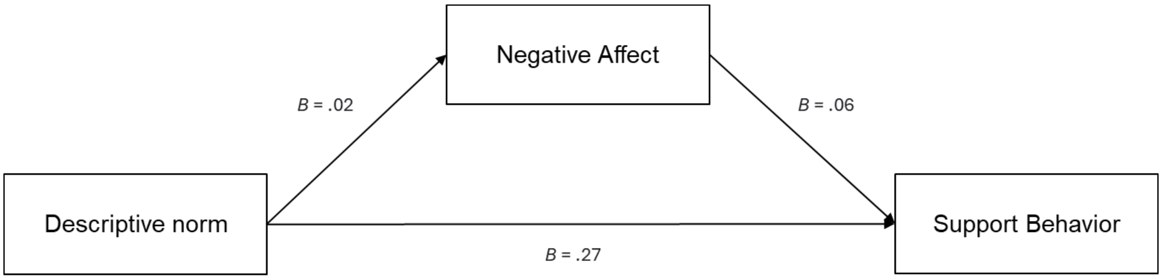
Figure 4C - *Negative Affect mediation above average (Conditional effects)*

SOLAR



Note: *Dependent variable: Support Behavior; R = .03; R^2 = .001 ($F_{(2,159)}$ = .06, p = .941); Indirect effect: B = -.001, BootSE = .03, BootLLCI = -.03, BootULCI = .07.*

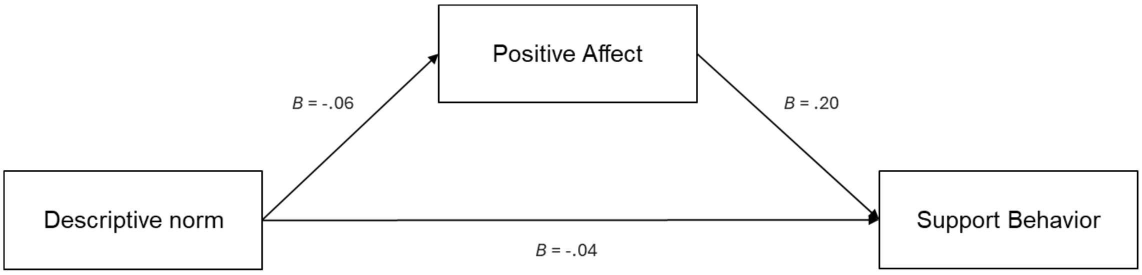
HYDROGEN



Note: *Dependent variable: Support Behavior; R = .09; R^2 = .001 ($F_{(2,198)}$ = .82, p = .443); Indirect effect: B = -.001, BootSE = .02, BootLLCI = -.04, BootULCI = .03.*

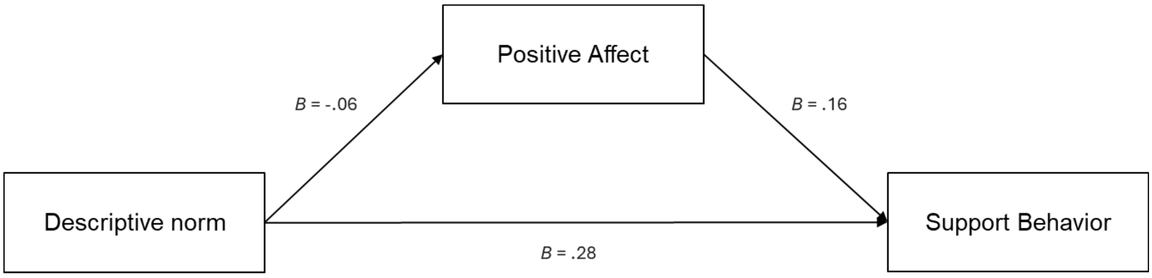
Figure 5C - *Positive Affect mediation above average (Conditional effects)*

SOLAR



Note: *Dependent variable: Support Behavior; R = .15;* R^2 *= .02 (*$F_{(2,159)}$ *= 1.88, p = .155); Indirect effect: B = -.01, BootSE = .04, BootLLCI = -.09, BootULCI = .05.*

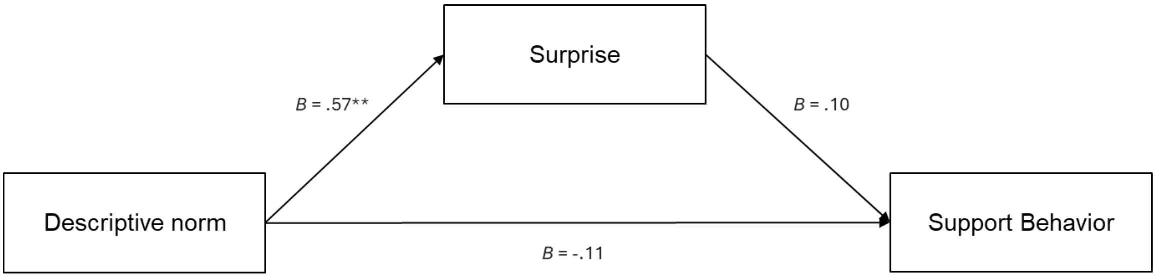
HYDROGEN



Note: *Dependent variable: Support Behavior; R = .13;* R^2 *= .02 (*$F_{(2,198)}$ *= 1.63, p = .198); Indirect effect: B = -.01, BootSE = .03, BootLLCI = -.09, BootULCI = .02.*

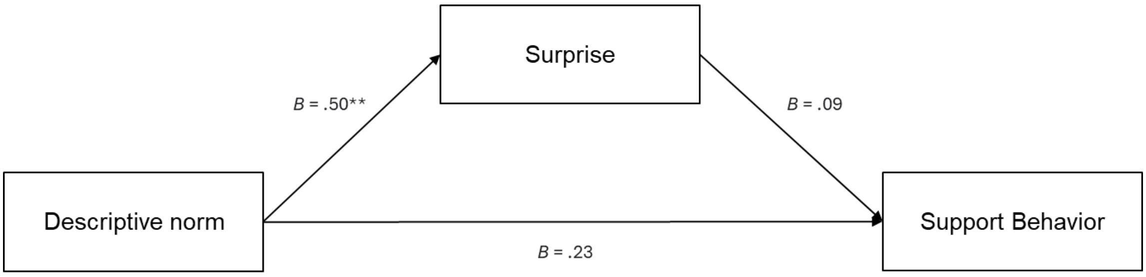
Figure 6C - *Surprise mediation above average (Conditional effects)*

SOLAR



Note: *Dependent variable: Support Behavior; R = .09;* R^2 *= .01 (*$F_{(2,159)}$ *= .64, p = .531); Indirect effect: B = .05, BootSE = .06, BootLLCI = -.05, BootULCI = .18.*

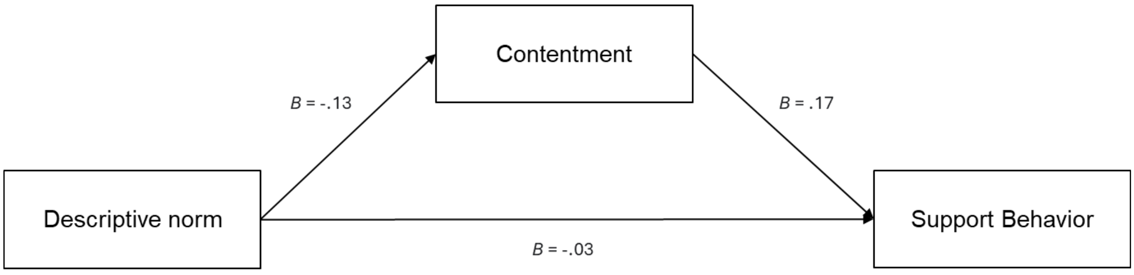
HYDROGEN



Note: *Dependent variable: Support Behavior; R = .11;* R^2 *= .01 (*$F_{(2,198)}$ *= 1.22, p = .299); Indirect effect: B = .04, BootSE = .05, BootLLCI = -.05, BootULCI = .15.*

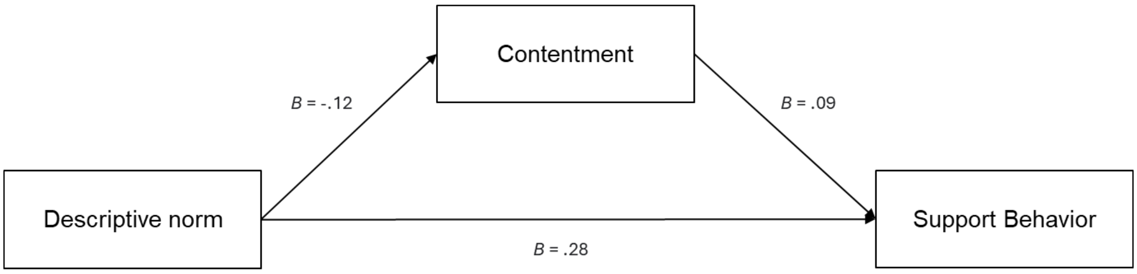
Figure 7C - *Contentment mediation above average (Conditional effects)*

SOLAR



Note: *Dependent variable: Support Behavior; R = .15;* $R^2 = .02$ *(*$F_{(2,159)} = 1.88$*, p = .155); Indirect effect: B = -.02, BootSE = .04, BootLLCI = -.11, BootULCI = .04.*

HYDROGEN



Note: *Dependent variable: Support Behavior; R = .11;* $R^2 = .01$ *(*$F_{(2,198)} = 1.27$*, p = .284); Indirect effect: B = -.01, BootSE = .03, BootLLCI = -.08, BootULCI = .02.*