UNIVERSIDADE FEDERAL DE PERNAMBUCO

CENTRO ACADÊMICO DO AGRESTE

PROGRAMA DE PÓS-GRADUAÇÃO EM GESTÃO, INOVAÇÃO E CONSUMO

Sustainable Choices: How heuristics influence attitude and adoption intention toward solar energy

Vinícius Azevedo Barbosa

Caruaru

2025

VINÍCIUS AZEVEDO BARBOSA

Sustainable Choices: How Heuristics Influence Attitudes and Adoption Intentions Toward Solar Energy

Dissertation presented to the Graduate Program in Management, Innovation, and Consumption at the Federal University of Pernambuco as a partial requirement for obtaining the master's degree in management, Innovation, and consumption.

Concentration area: Innovation, Culture, and Consumption in Local Business Management.

Advisor: Prof. Dr. Marconi Freitas da Costa.

Caruaru

2025

Barbosa, Vinícius Azevedo.
Sustainable Choices: How Heuristics Influence Attitudes and Adoption Intentions Toward Solar Energy / Vinícius Azevedo Barbosa. - Caruaru, 2025.
110 f.: il.

Dissertação (Mestrado) - Universidade Federal de Pernambuco, Centro de Acadêmico do Agreste, Programa de Pós-Graduação em Gestão, Inovação e Consumo, 2025.
Orientação: Prof. Dr. Marconi Freitas da Costa.
Inclui referências e apêndices.

1. Solar energy adoption; 2. Heuristics; 3. Consumer Behavior; 4. Energy transition. I. Costa, Marconi Freitas da. II. Título.

UFPE-Biblioteca Central

VINÍCIUS AZEVEDO BARBOSA

Sustainable Choices: How Heuristics Influence Attitudes and Adoption Intentions Toward Solar Energy

Dissertation presented to the Graduate Program in Management, Innovation, and Consumption at the Federal University of Pernambuco as a partial requirement for obtaining the master's degree in management, Innovation, and consumption.

Concentration area: Innovation, Culture, and Consumption in Local Business Management.

Advisor: Prof. Dr. Marconi Freitas da Costa.

Approved at: 07/02/2025

Defense Committee

Prof. Dr. Marconi Freitas da Costa **(Advisor)**
Universidade Federal de Pernambuco

Prof. Dr. Cristiane Salomé Ribeiro Costa **(Internal Examiner)**
Universidade Federal de Pernambuco

Prof. Dr. Ming-Yi Wu **(External Examiner)**
Northeastern University-College of Professional Studies

This thesis is dedicated to my parents, who instilled in me the value of education and perseverance.

GRATITUDE MESSAGE

My gratitude extends first and foremost to my family and friends, whose steadfast support guided me through both triumphs and obstacles along this academic path. My parents, Aurílio and Zelia, and my siblings, Camila and Gabriel, constantly reaffirmed the value of perseverance. Their patience and advice were indispensable in helping me find balance between personal life and scholarly commitments

This accomplishment would not have been possible without the mentorship of Prof. Dr. Marconi Costa, who continually challenged me to push beyond my academic comfort zone. I especially appreciate his guidance on research development and critical thinking, essential factors in earning this title. His willingness to share expertise, particularly on consumer behavior and sustainability gave me the confidence to tackle complex research questions.

I am also deeply indebted to Professors Lindenberg Farias, Cristiane Costa, Julio Cezar Ferro, and Nelsio Rodrigues at UFPE-CAA. Their impactful classes have been instrumental in my academic development. Professor Farias' enthusiastic approach to research design sparked my own curiosity, while Professor Costa's insightful guidance in consumer behavior provided a strong foundation for my research. Professor Ferro's expertise in advanced statistical methods, particularly Structural Equation Modeling, equipped me with essential analytical tools. And Professor Rodrigues's thought-provoking discussions fostered an environment of intellectual exploration that broadened my perspectives.

I am deeply grateful to Mayara Santos, whose friendship and support extended beyond her role as an exceptional administrative officer, providing valuable insights and encouragement. My sincere thanks also go to Amanda Farias, whose resilience and understanding were invaluable during challenging times. I appreciate the camaraderie of my classmates and the support of friends both new and old, who helped me persevere throughout this journey.

Agradecimentos

Meu agradecimento vai, em primeiro lugar, à minha família e amigos, cujo apoio constante me guiou tanto nos triunfos quanto nos obstáculos ao longo desta trajetória acadêmica. Meus pais, Aurílio e Zelia, e meus irmãos, Camila e Gabriel, reafirmaram continuamente o valor da perseverança. Seus conselhos e paciência foram indispensáveis para me ajudar a encontrar o equilíbrio entre a vida pessoal e os compromissos acadêmicos.

Esta conquista não teria sido possível sem a mentoria do Prof. Dr. Marconi Costa, que me desafiou a ir além da minha zona de conforto acadêmica. Agradeço especialmente sua orientação no desenvolvimento da pesquisa e no pensamento crítico, fatores essenciais para a obtenção deste título. Sua disposição em compartilhar seus conhecimentos, especialmente sobre comportamento do consumidor e sustentabilidade, me deu a confiança necessária para abordar questões complexas de pesquisa.

Sou também profundamente grato aos professores Lindenberg Farias, Cristiane Costa, Julio Cezar Ferro e Nelsio Rodrigues da UFPE-CAA. Suas aulas impactantes foram instrumentais no meu desenvolvimento acadêmico. O entusiasmo do Professor Lindenberg pelo planejamento de pesquisa despertou minha curiosidade, enquanto as aulas da Profº Cristiane em comportamento do consumidor me forneceram uma base sólida para minha pesquisa. A expertise do Professor em Modelagem de Equações Estruturais, me equipou com ferramentas analíticas essenciais. E as discussões instigantes do Professor Rodrigues promoveram um ambiente de exploração intelectual que ampliou minhas perspectivas.

Agradeço profundamente a Mayara Santos, cuja amizade e apoio se estenderam além de seu papel como excepcional funcionária administrativa, proporcionando-me valiosas percepções e incentivo. Meus sinceros agradecimentos também a Amanda Farias, cuja resiliência e compreensão foram inestimáveis em momentos desafiadores. Agradeço a camaradagem dos meus colegas de classe e o apoio de amigos, novos e antigos, que me ajudaram a perseverar ao longo desta jornada.

“The sunshine bores the daylights out of me”
Jagger and Richards

ABSTRACT

The adoption of solar energy transcends financial considerations, reflecting complex psychological processes that influence consumer attitudes and behaviors. This study examines how cognitive heuristics—availability, representativeness, and anchoring—interact with the Theory of Planned Behavior (TPB) to shape solar energy adoption in urban households in northeastern Brazil. Using data from 380 respondents, analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM), the research identifies the availability heuristic as the most influential predictor of attitude, emphasizing the impact of vivid, relatable information. Anchoring, while secondary, highlights how initial perceptions of cost shape subsequent decisions. In contrast, representativeness exhibited no significant effect, challenging assumptions about the role of stereotypes in consumer behavior.

The findings highlight the necessity of tailored communication strategies that leverage relatable narratives and address cognitive biases to bridge gaps in consumer perception. By focusing on these psychological dimensions, this research provides actionable insights for policymakers and marketers aiming to enhance solar adoption rates. The study contributes to the global discourse on renewable energy by offering a nuanced understanding of decision-making processes, particularly in the context of emerging economies. Aligning with the United Nations Sustainable Development Goals (SDGs), this work underscores the importance of psychological factors in driving the transition to sustainable energy systems..

Keywords: Solar energy adoption, Heuristics, Theory of planned behavior, energy transition.

TABLES SUMMARY

ABREVIATIONS AND ACRONYMS

AVE - Average Variance Extracted

CFA - Confirmatory Factor Analysis

CFI - Comparative Fit Index

CR - Composite Reliability

DESA - United Nations Department of Economic and Social Affairs

DWLS - Diagonally Weighted Least Squares

EFA - Exploratory Factor Analysis

GBA - Greater Bay Area

HTMT - Heterotrait-Monotrait Ratio

ICF - Informed Consent Form

IPCC - Intergovernmental Panel on Climate Change

JASP - Statistical Software

KOPA - M-KOPA Solar Program

LGPD - Lei Geral de Proteção de Dados

ML - Maximum Likelihood

PEBI - Pro-Environmental Behavioral Intentions

PLS - Partial Least Squares

PLS-SEM - Partial Least Squares Structural Equation Modeling

PPGIC-UFPE - Programa de Pós-Graduação em Gestão, Inovação e Consumo

PV - Photovoltaic

RDWLS - Robust Diagonally Weighted Least Squares

RMSEA - Root Mean Square Error of Approximation

SDG - Sustainable Development Goals

SEM - Structural Equation Modeling

SETO - Solar Energy Technologies Office

SRMR - Standardized Root Mean Square Residual

SSRN - Social Science Research Network

TAM - Technology Acceptance Model

TLI - Tucker-Lewis Index

TPB - Theory of Planned Behavior

TRI - Technology Readiness Index

ULS - Unweighted Least Squares

UN - United Nations

VIF - Variance Inflation Factor

TABLE OF CONTENTS

1. Introduction

Mitigating and adapting to climate change requires a comprehensive approach that includes strategies to reduce greenhouse gas emissions, adapt to climate impacts, and foster international cooperation (Marquardt et al., 2023). Solar energy adoption, particularly in the residential sector, is not just a local effort but a critical component of global efforts to mitigate global warming (Ghosh & Krishnaswamy, 2024). Despite its recognized benefits, the adoption of solar energy in urban households, especially in emerging economies like Brazil, remains below expectations (Queiroz et al., 2020; BEN 2023). This is surprising given that solar energy can provide reliable power even in remote areas, reduce dependency on traditional energy sources, and offer a sustainable solution to rising energy demands, technology skepticism, perceived inconveniences and lack of knowledge play a significant role in this scenario (Leduchowicz-Municio et al., 2023).

The escalating climate crisis demands urgent action. The transition to renewable energy sources like solar power plays a critical role. Recent events, such as droughts in Europe, heat waves in Asia, and changing rainfall patterns in Brazil (World Meteorological Organization, 2024), underscore the urgent need for this energy transition (Gosnell & Bazilian, 2021). These occurrences highlight the need for a paradigm shift in consumption patterns, particularly concerning energy use. They emphasize the necessity of reevaluating and modifying consumer behavior, with a specific focus on the transition towards more sustainable energy sources. However, there is a limited understanding of the psychological factors influencing consumer decision-making in this area. Existing research focuses primarily on economic and technical barriers (Sadler-Smith, 2023), while cognitive heuristics that promote engagement in sustainable practices are less studied.

To effectively address these psychological barriers, a deeper understanding of the decision-making process related to solar energy adoption is crucial. The importance of the study relies on its capacity to provide insights for policy marketers to promote effective campaigns for the solar energy adoption uptake to develop a more sustainable energy matrix in Brazil and let the county be less dependent on hydroelectric sources.

Policy initiatives worldwide, such as California's Solar Rooftop Program, India's Solar Electrification Program, and Kenya's M-KOPA Solar initiative, highlight the transformative potential of solar energy adoption (Armenia et al., 2022; George et al., 2019; Kumar et al., 2023). These programs have empowered homeowners, brought solar energy to remote villages, and improved the quality of life for thousands of families while reducing greenhouse gas emissions. However, promoting wider adoption requires addressing the psychological factors that influence consumer choices.

With these challenges in perspective, global collaboration becomes vital in addressing climate change (Santika et al., 2020), with international agreements like the Paris Agreement playing a key role (Gurtner & Moser, 2024). Facilitating technology transfer and capacity building, particularly in developing countries, ensures widespread adoption of climate-resilient technologies and practices (Martin Klein et al., 2017). Previous studies such as Wolske (2020) provide valuable insights into the motivations and barriers households face in adopting solar systems, such as reduced energy cost, Environmental awareness, social norms and reputation among peers, aligning with the current research's focus on urban residential contexts in populations of different incomes.

The current proposal presents a novel approach to investigating urban households' adoption of solar energy systems. It focuses on the psychological factors influencing consumer decision-making (Von Gal et al., 2024). By integrating Heuristics and Prospect Theory (Kahneman & Tversky, 1979; 1974), by using them as complementary frameworks to analyze different aspects of the same phenomenon: consumer decision-making regarding solar energy adoption. The proposal seeks to bridge the identified gap, by exploring the influence of heuristics, the study seeks to uncover the underlying mechanisms that drive individuals' attitudes and intentions toward solar energy adoption.

Through this comprehensive analysis, the research will provide constructive insights that can contribute to the ongoing discourse on sustainable energy transition (Carpino et al., 2022). The urgency of the global energy transition has been highlighted at COP 28 in 2023, with the 'Global Renewables and Energy Efficiency Pledge' aiming to triple renewable energy capacity by 2030, and subsequently COP 29, in 2024 (UNDESA, 2024). This international commitment underscores the need for research into the factors driving renewable energy adoption, particularly in emerging economies like Brazil, which hold significant potential but also face unique challenges.

To effectively translate these global commitments into tangible action, it becomes essential to delve into the individual decision-making processes that ultimately drive the adoption of renewable energy technologies. This requires understanding not only the economic and technical considerations but also the psychological factors that influence consumer choices. Therefore, this study adopts the Theory of Planned Behavior (TPB) (Ajzen, 1991) in complement with the heuristic and prospect theory to investigate the interplay of intentions, attitudes, and other cognitive factors in shaping solar energy adoption.

TPB posits that individual behaviors are driven by intentions and attitudes (Ajzen, 1996, 2008, 2015, 2020; Martin Fishbein et al., 2011). To understand the nuances of solar energy adoption, this framework has been extended and applied in various studies. For instance, Alsulami et al. (2024) investigated the factors influencing Saudi homeowners' intentions to adopt solar energy, while Hasheem et al. (2022) explored similar intentions among households in Pakistan, integrating the Technology Readiness Index (TRI) with TPB.

Further refining the understanding of solar energy adoption, Schulte et al. (2022) employed meta-analytic structural equation modeling to synthesize multiple studies on residential photovoltaic (PV) adoption, emphasizing the role of perceived benefits and intentions through the lens of TPB. Similarly, Fauzi et al. (2023) conducted a bibliometric analysis, identifying key themes like innovation diffusion and adoption motivations, again using TPB as a framework. Harun et al. (2022) extended the application of TPB to examine consumer purchasing behavior of energy-efficient appliances, finding that energy-efficient behavior, subjective norms, and perceived behavioral control significantly influence purchase intentions, insights that can be extended to solar energy adoption.

Complementing the TPB framework, this study incorporates the insights of Maibach (2019) on the importance of cognitive heuristics in climate change communication. By making information relatable and illustrating clear cause-and-effect relationships, communicators can enhance understanding and motivate sustainable practices. Additionally, the work of Klein and Deissenroth (2017) provides a nuanced perspective on the decision-making process behind residential solar PV adoption by applying prospect theory (Kahneman & Tversky, 1979). This theory suggests that households' investment decisions are influenced not only by profitability but also by the perceived change in profitability compared to the status quo, offering a more accurate prediction of solar PV adoption behavior (Gigerenzer, 2008) than traditional expected utility models (Moscati, 2023; Schoemaker, 1982).

This research seeks to bridge a gap in the existing literature by exploring the influence of different heuristics, such as availability and representativeness, on the decision-making process of adopting solar energy. By gaining a comprehensive understanding of these cognitive processes, the study aims to contribute to the development of more effective policies and interventions to promote solar energy adoption.

In the upcoming topics, we will introduce our research objectives, discuss the theoretical framework, and outline the methodology employed to investigate the impact of heuristics on the attitude toward the adoption of solar energy.

2. Objectives

2.1 General Objective

To investigate how prospect theory (representativeness, availability, anchoring, and adjustment, choice heuristics) influence consumer attitudes and intentions regarding the adoption of solar energy.

2.2 Specific Objectives

- Analyze the direct influences of the representativeness, availability, anchoring, and adjustment heuristics on consumer attitudes and intentions toward solar energy adoption in urban households.
- Verify the relationships between heuristics, attitudes, and intentions toward solar energy adoption.
- Assess the mediating role of choice heuristics in determining attitudes and intentions for solar energy adoption in urban households.

2.3 Theoretical and Practical Justifications

This research integrates the Theory of Planned Behavior, Heuristics, and Prospect Theory to provide a comprehensive framework for understanding how individuals make decisions about solar energy adoption, particularly how cognitive shortcuts influence judgments and behaviors in this context. By applying these theories, the study aims to uncover how consumers form attitudes and intentions based on limited information and perceived risks and benefits (Kause et al., 2019). Towards solar energy adoption.

This integrated approach offers a novel perspective by examining the interplay between motivational factors (TPB), cognitive biases (Prospect Theory), and heuristics. This combined lens provides a more nuanced understanding of solar energy adoption decisions than previous models that focused primarily on economic or technical factors. The study addresses a critical gap in behavioral economics and consumer psychology, extending the understanding of consumer behavior beyond economic and technical barriers (Strupeit & Palm, 2016). This comprehensive analysis of the factors shaping consumer decisions is necessary to develop a fuller picture of the influences on solar energy adoption (Sadler-Smith, 2023). Understanding the factors that influence consumer decisions related to solar energy, marketers and policymakers can develop more effective strategies to encourage the adoption of other renewable energy technologies, contributing to the transition towards a more sustainable energy system.

By focusing on solar energy adoption in Brazil, a leading emerging economy in the Global South, this study provides valuable insights into the role of heuristics in shaping consumer choices within a developing nation context. The findings contribute to a nuanced understanding of sustainable energy choices and align with the United Nations Sustainable Development Goals (SDGs), particularly those related to affordable and clean energy (SDG 1 7), industry, innovation, and infrastructure (SDG 9), responsible consumption and production (SDG 12), and climate action (SDG 13) (UNDESA, 2023).

From a practical standpoint, this research addresses the suboptimal solar energy adoption rates in urban households, particularly in emerging economies like Brazil, where adoption rates remain below expectations despite the recognized benefits of solar energy (Leduchowicz-Municio et al., 2023). Understanding the cognitive factors influencing consumer decisions can help design more effective interventions to boost adoption rates (Gigerenzer, 2008). For instance, recognizing how representativeness, availability, anchoring, and adjustment heuristics affect decision-making can inform strategies to overcome these psychological barriers (Mutumbi et al., 2024).

This research has significant implications for policy initiatives. By identifying the specific heuristics that influence solar energy adoption decisions, policymakers can design interventions that counteract biases, such as framing incentives to mitigate loss aversion or providing clear and accessible information to enhance obtainability. The research can inform the development of comprehensive and impactful policies that empower homeowners to install solar panels, generate clean energy, and reduce electricity bills, enhancing community resilience and energy independence (Armenia et al., 2022).

Furthermore, the study can enhance communication strategies for promoting solar energy adoption. Understanding how cognitive heuristics shape consumer attitudes and intentions allows stakeholders to develop targeted communication strategies that resonate with consumers and promote solar energy adoption intention (Agarwal et al., 2023). For example, leveraging the representativeness heuristic, marketers can associate solar energy with positive attributes like innovation and technological advancement. Effective communication is crucial for increasing consumer engagement and facilitating the transition to renewable energy sources (Maibach, 2019). By employing strategies that address heuristics, communicators can enhance the effectiveness of their messages and promote higher adoption rates (Palm & Lantz, 2020).

In conclusion, this research holds both theoretical and practical significance. By addressing a critical gap in understanding the cognitive factors influencing solar energy adoption, it offers valuable insights that can inform policymaking, enhance communication strategies, and ultimately contribute to the global transition towards sustainable energy sources. By integrating well-established psychological theories with practical considerations, the study aims to enhance global efforts to mitigate climate change and support the adoption of renewable energy sources, aligning with international agreements like the Paris Agreement and contributing to achieving sustainable development goals (Santika et al., 2020; Gurtner & Moser, 2024).

3. Theoretical Framework

This research employs an integrated framework to investigate the factors influencing solar energy adoption, drawing upon key constructs from the Theory of Planned Behavior (TPB) (Ajzen, 1991), Prospect Theory (Kahneman & Tversky, 1979), and the heuristics literature. By examining the interplay between these variables—availability heuristic, representativeness heuristic, anchoring and adjustment heuristic, attitude, and intention toward solar energy adoption—the study aims to provide a comprehensive understanding of the decision-making process in this domain (Kause et al., 2019). This integrated approach is particularly relevant because previous research has often focused on either motivational factors (TPB) and cognitive biases (Prospect Theory) in isolation, but this study aims to examine their interplay along with the influence of heuristics.

This integrated approach offers a novel perspective by combining insights from different theoretical lenses. The TPB, with its focus on attitudes, subjective norms, and perceived behavioral control, provides a foundation for understanding the motivational factors driving behavioral intentions (Ajzen, 1991). Prospect Theory sheds light on how individuals perceive and evaluate potential gains and losses, offering insights into the risk perception and decision-making biases that might influence solar energy adoption (Kahneman & Tversky, 1979). The heuristics literature further enriches this framework by examining the role of cognitive shortcuts in simplifying complex decisions.

Specifically, this study examines how the availability heuristic, representativeness heuristic, and anchoring and adjustment heuristic influence solar energy adoption. The availability heuristic suggests that individuals assess the likelihood of an event based on the ease with which instances or occurrences come to mind. In the context of solar energy, readily available information, such as success stories or visible installations in one's community, might positively influence attitudes and intentions toward adoption. The representativeness heuristic suggests that individuals categorize and make judgments based on similarity to prototypes or stereotypes. If solar energy aligns with an individual's prototype of an innovative and environmentally friendly technology, it might lead to more favorable attitudes and intentions. The anchoring and adjustment heuristic suggests that individuals rely heavily on an initial piece of information (the "anchor") when making decisions, even if that information is not necessarily relevant or accurate. In the context of solar energy, initial cost estimates or perceived complexity of installation might serve as anchors, influencing subsequent evaluations and decisions.

By examining the interplay between these heuristics, attitudes, and intentions, the study aims to uncover the underlying mechanisms that drive solar energy adoption decisions. For instance, the research will investigate how the availability heuristic might interact with attitudes to shape intentions, or how anchoring and adjustment might influence the perceived value of solar energy investments.

This study aims to contribute to the growing body of literature on sustainable energy transitions by providing a robust and nuanced understanding of the psychological and cognitive factors influencing solar energy adoption. The findings are expected to have valuable implications for promoting renewable energy sources and mitigating climate change. Overall, this integrated framework offers a promising approach to understanding the complexities of solar energy adoption decisions and developing effective interventions to promote sustainable energy choices.

3.1 Introduction to the Theory of Planned Behavior

The theory of planned behavior posits that intentions, shaped by attitude, subjective norms, and perceived behavioral control, play a crucial role in predicting actual behavior (Ajzen, 1991). Intention represents an individual's readiness to engage in specific behaviors. In the context of solar energy adoption, numerous studies have applied the TPB framework (Duan et al., 2023; Gansser & Reich, 2022; Tan et al., 2023; Vu et al., 2023), highlighting the relationship between adoption intentions and factors like resource availability and perceived behavioral control (Schulte et al., 2022).

For instance, Fathima et al. (2022) identified attitude, perceived behavioral control, and energy concern as crucial predictors of consumers' intentions to purchase solar energy products, while Filgueira et al. (2022) emphasized environmental influences and financial benefits in driving solar energy adoption intentions in Brazil. However, Filgueira et al. (2022) found that perceived social benefits were not a significant factor, contrasting with findings from Korcaj et al. (2015) in Germany. Fazal et al. (2023) offered a comprehensive analysis of renewable energy adoption among low-income households in Malaysia, examining various factors influencing the intention to adopt renewable energy, including solar energy and palm oil biomass.

Several studies have explored solar energy adoption intentions in developing countries. Mwanza & Mbohwa (2023) investigated the factors influencing households' intention to adopt solar energy technologies in Zambia. Mutumbi et al. (2024) explored the barriers to adopting solar energy in South Africa, focusing on social, political, and technical barriers. Tanveer et al. (2021) applied the TPB in Pakistan, highlighting the lack of knowledge and awareness among consumers, suppliers, and policymakers as significant barriers to solar energy adoption.

Xu et al. (2024) examined the factors influencing residents' intentions to adopt solar energy in the Greater Bay Area (GBA) of China, utilizing an extended TPB model to explore the discrepancy between residents' intentions and actual behaviors.

Five meta-analyses on renewable energy technologies, with an emphasis on solar energy, have highlighted the importance of the intention variable. Each study defines intention uniquely, demonstrating the construct's vastness and contextual nature for renewable energy consumers.

Schulte et al. (2022) focused on the intention to adopt residential PV systems, finding medium to large correlations between intention and factors such as environmental concern, perceived benefits, and subjective norms. Ghosh & Satya Prasad (2024) examined pro-environmental behavioral intentions (PEBI) related to solar PV adoption, finding moderate positive correlations between environmental factors and PEBI. Best et al. (2023) focused more on actual adoption rather than intention, providing insights into methodological considerations. Gangakhedkar & Karthik (2024) examined purchase intention for renewable energy technologies more broadly, applying both TPB and the Technology Acceptance Model (TAM).

These meta-analyses collectively underscore the robustness of the TPB model in understanding solar energy adoption intentions across various contexts and emphasize the influence of factors such as environmental concerns, perceived benefits, and social norms. This comprehensive literature review has revealed a range of variables that influence purchase intentions for renewable energy technologies, providing a robust framework for researchers.

This research will solely focus on measuring the adoption intention for several factors: 1. Per the Theory of Planned Behavior (TPB), the intention is posited as the most proximal and robust predictor of subsequent behavior (Ajzen, 1991). Measuring intentions is more feasible and less resource-intensive than tracking actual adoption behavior over time; 2? measuring intentions offers a more pragmatic and resource-efficient approach than longitudinal tracking of actual adoption behavior. This allows for a larger sample size and more comprehensive data collection within the study's constraints.

Having established the significance of intentions in predicting solar energy adoption, it is crucial to delve deeper into the concept of attitudes toward solar energy adoption. Attitudes play a pivotal role in shaping intentions. The following section will explore how attitudes are formed, the factors influencing them, and their impact on the adoption of solar energy.

3.2 Attitude towards the Adoption of Solar Energy

Within the Theory of Planned Behavior (TPB), attitude serves as a critical foundation for understanding how individuals evaluate and form intentions towards specific behaviors. In the context of solar energy adoption, attitude reflects an individual's overall assessment of this technology, encompassing their beliefs, emotions, and behavioral tendencies. This section delves into the multifaceted nature of attitudes towards solar energy and their profound influence on adoption intentions.

Extensive research has explored attitudes towards solar energy adoption, revealing the complex interplay of factors influencing individuals' evaluations and beliefs (Abreu et al., 2019; Schulte et al., 2022). These studies highlight the critical role of attitude as a precursor to intention, which signifies one's readiness to adopt solar technologies (Ajzen, 1991, 2012).

One notable phenomenon is the attitude-behavior gap in household solar energy system adoption, as identified by Loveldy (2021). This study found that while many individuals exhibited positive attitudes toward solar technology, they did not adopt it, highlighting the influence of barriers such as lack of awareness, financial constraints, and social norms. Similarly, Abreu et al. (2019) emphasized the significant role of subjective norms in shaping adoption intentions.

Muwanga et al. (2024) investigated the cognitive, affective, and conative dimensions of attitudes, revealing that all three significantly influenced adoption intentions among households in Uganda. This multidimensional approach highlights the importance of considering different aspects of attitudes. Other studies, such as those by Wolske et al. (2020) and Korcaj et al. (2015), have explored the impact of peer reviews, opinions, and social considerations on the adoption of solar energy systems.

However, the influence of attitudes on adoption intentions may vary depending on the specific population. Lundheim et al. (2021) found that attitudes had only a marginally significant impact on intentions among individuals already interested in solar panels in Nordic countries, suggesting that other factors may become more salient in driving their adoption decisions when individuals are already positively inclined towards solar energy. Environmental awareness and knowledge also play a crucial role in shaping attitudes, as demonstrated by He & Veronesi (2017) in their study of consumers' buying intentions for solar energy in China.

Furthermore, Vibrans et al. (2023) used milieu segmentation to explain variations in the impact of attitudes on adoption intentions across different social groups in Germany. This underscores the need to account for the diversity of attitudes when examining adoption intentions. Cultural and regional differences also come into play, with studies in Europe and North America often highlighting environmental consciousness, while in emerging economies, economic benefits and energy security are more prominent factors (Jiang et al., 2023).

Barriers such as high initial costs and lack of information can negatively impact attitudes, while facilitators like government incentives and successful case studies can significantly improve attitudes (Smith et al., 2023). Quantitative evidence from Loveldy (2021) supports these findings.

In summary, attitudes are fundamental in shaping consumers' intentions to adopt solar energy technology. By effectively analyzing and addressing consumers' attitudes, stakeholders can drive the transition towards sustainable energy practices. Integrating the Theory of Planned Behavior with heuristic variables as predecessors of attitude offers a promising path for understanding attitude formation and its implications for solar energy adoption intention.

Based on the reviewed literature and the understanding of the crucial role of attitudes in shaping intentions, the following hypothesis is proposed:

H1: Attitude positively and directly influences intention toward solar energy adoption

Integrating the Theory of Planned Behavior with heuristic variables as predecessors of attitude offers a promising path for understanding attitude formation and its implications for solar energy adoption intention. Building upon the understanding of attitudes and their influence on solar energy adoption intentions, the next section explores the role of Prospect Theory and heuristics in shaping decision-making, specifically how heuristics influence the formation of attitudes and subsequent intentions towards solar energy. It investigates how these cognitive processes can simplify complex choices, framing perceptions of gains and losses, and ultimately influencing individuals' decisions regarding sustainable energy solutions.

3.3 Prospect Theory and Heuristics in Decision-Making

Heuristics are cognitive shortcuts that simplify complex or uncertain information processing (Smriti Pathak et al., 2023; Tversky & Kahneman, 1974). In sustainability, heuristics help individuals navigate the intricacies of environmentally conscious decision-making, such as evaluating renewable energy options. For instance, the availability heuristic allows consumers to judge solar energy's feasibility based on vivid examples, like neighbors' successful installations. Similarly, the representativeness heuristic leads individuals to perceive products as "eco-friendly" based on green labels, aligning with their mental prototypes of sustainability. These cognitive shortcuts enable quicker judgments without exhaustive deliberation, facilitating efficient responses to complex scenarios (Gigerenzer et al., 2015).

Under Prospect Theory, gains and losses are assessed relative to a reference point rather than absolute terms. For example, homeowners considering solar panel installations may perceive upfront costs as significant losses compared to their current energy expenses but frame long-term savings as substantial gains, especially when tied to narratives of reduced energy bills. This relativity highlights how heuristics like anchoring and availability shape perceptions of value and risk (Kruglanski et al., 1983). While early studies focused on heuristics as sources of error (Arie et al., 1983; Love et al., 2023), recent research recognizes their adaptability and efficiency in decision-making.

Initially, heuristics were seen as cognitive biases leading to suboptimal decisions, particularly in unfamiliar contexts (Kurz-Milcke & Gigerenzer, 2007; Yu et al., 2014). However, subsequent research demonstrates that reliance on heuristics often yields outcomes as accurate as those derived from statistical reasoning (Gigerenzer & Gaissmaier, 2011). Heuristics function as cognitive saving mechanisms, reducing complexity and aiding individuals in navigating challenging scenarios efficiently.

Recent studies further illustrate heuristics' adaptive potential. Meinert & Krämer (2022) found that expertise heuristics, which rely on perceived authority or expertise to evaluate information, significantly reduce the time needed to assess credibility on social media platforms. Contrary to assumptions about age-related differences in heuristic use, Taylor et al. (2023) revealed no evidence that older adults rely less on heuristics. Instead, personal experiences significantly influence heuristic application, indicating consistent reliance across age groups. Beyond individual decisions, heuristics shape organizational strategies, including internationalization processes for small and medium-sized enterprises (SMEs) (Jindal & Shrimali, 2022; Nittymes, 2020).

The evolving discourse on heuristics highlights their dual nature: while they can introduce biases, they also serve as adaptive tools in decision-making. For example, the availability heuristic, often associated with overestimating the likelihood of vivid events, aids in processing accessible information effectively. Similarly, the representativeness heuristic allows individuals to draw meaningful parallels, such as homeowners considering solar energy based on their peers' success stories (Amos Tversky et al., 1981; Kahneman & Frederick, 2002). These shortcuts help individuals align decisions with their preferences and goals efficiently (Daniel Kahneman & Kahneman, 2006).

In the context of climate change, heuristics are particularly relevant as consumers face complex information about environmental issues and their consumption choices. The availability heuristic may lead individuals to overestimate the impact of vivid but infrequent events, like oil spills, while underestimating the cumulative effects of routine behaviors, such as daily driving. Similarly, the representativeness heuristic might prompt choices based on "eco-friendly" labels without verifying the products' actual environmental impact. These tendencies highlight the importance of designing strategies that account for heuristic-driven behaviors to promote sustainable consumption.

Leveraging heuristics offers opportunities for promoting sustainability. Policymakers and marketers can reduce perceived complexities surrounding solar energy adoption by employing intuitive tools and messages. Narratives and testimonials can enhance the availability heuristic, making solar energy benefits more tangible. Framing default options for renewable energy plans or providing clear, visually accessible metrics on energy savings can nudge consumers toward sustainable choices. Ethical application of these strategies is essential to empower consumers to make informed decisions aligned with their values and long-term goals (Palm & Eriksson, 2018). A nuanced understanding of heuristics within decision-making frameworks can drive strategies to mitigate the climate crisis and foster a sustainable energy future.

3.3.1 Availability Heuristic

The availability heuristic refers to the tendency to judge the likelihood or frequency of an event based on the ease with which relevant instances come to mind (Tversky & Kahneman, 1973). In the solar energy context, the availability of information about the benefits of solar power and examples of successful adoption can significantly influence individuals' perceptions and decisions.

Empirical studies have demonstrated the impact of the availability heuristic on solar energy adoption. For instance, research has shown that exposure to positive media coverage and social influence from peers who have adopted solar panels can increase individuals' likelihood of considering solar energy (Abreu et al., 2019; Rai & Robinson, 2013). Examples of successful campaigns that have used the availability heuristic to promote the adoption of solar energy include the U.S. Department of Energy's Solar Energy Technologies Office (SETO) Equitable Access to Solar Energy portfolio, which aims to tackle barriers to greater solar adoption and increase access to affordable solar electricity for all U.S. consumers, especially those who lack access to electricity, particularly in developing countries.

SETO's efforts include reducing energy costs, especially for households experiencing disproportionately high energy burdens, and supporting workforce development to create a more equitable clean energy future. The portfolio also supports research to improve rapid community solar development and other community-serving models to increase financial benefits, such as reduced energy bill burdens, workforce development, improved resiliency from distributed energy, and community wealth building.

The availability heuristic can influence an individual's evaluation (attitude) of solar energy by affecting the ease with which they can recall relevant information, such as the benefits and drawbacks of solar power. If individuals are frequently exposed to positive information about solar energy, such as news stories about successful solar installations or testimonials from satisfied solar panel owners, they may develop a more positive attitude toward solar energy.

In summary, by harnessing the availability heuristic, society can effectively promote solar energy adoption, leading to a range of benefits, including increased access to power, development of sustainable urban environments (Zebra et al., 2023), cleaner transportation options (Alogdianakis & Dimitriou, 2023), economic growth, and enhanced energy security (Brunet et al., 2022). Thus, it is hypothesized that:

H2: The availability heuristic directly and positively impacts attitudes toward solar energy adoption.

Having explored the influence of the availability heuristic, the study now turns to another important cognitive shortcut: the representativeness heuristic. This heuristic involves making judgments based on the similarity between an object or event and a mental prototype. In the context of solar energy adoption, how solar panels align with individuals' preconceived notions of environmentally friendly technology can significantly affect their attitudes and decisions. By examining the representativeness heuristic, the research proposal seeks to uncover additional layers of how cognitive shortcuts shape sustainable energy adoption.

3.3.2 Representativeness Heuristic

The representativeness heuristic involves judgments based on the perceived similarity between an object or event and a mental prototype (Kahneman & Tversky, 1972). In the context of solar energy adoption, individuals may perceive solar panels as fitting their mental image of an environmentally friendly technology, leading them to view solar energy more favorably and increasing their likelihood of adoption.

Kahneman and Frederick (2002) describe how the representativeness heuristic leads to attribute substitution, where more straightforward, more intuitive judgments replace complex ones. In the context of solar energy adoption, people may assess it based on stereotypes rather than a comprehensive evaluation. This simplified decision-making process can expedite the adoption of solar energy technologies (Alipour et al., 2021).

In conclusion, the representativeness heuristic is an adaptive strategy for simplifying decision-making processes regarding solar energy adoption (Gigerenzer et al., 2015). The heuristic expedites individual's overall assessment by recognizing solar energy as congruent with individuals' mental prototypes of desirable energy options (Shehata, Andersson, et al., 2021).

Given the potential of the representativeness heuristic to shape positive perceptions of solar energy and expedite adoption decisions, it is proposed that:

H3: The representativeness heuristic directly and positively impacts attitudes toward solar energy adoption.

Having examined the influence of the representativeness heuristic, the study now shifts its focus to the anchoring and adjustment heuristic. This heuristic highlights how an initial piece of information, or "anchor," can significantly shape subsequent judgments and decisions. In the context of solar energy, the upfront cost often acts as a powerful anchor, impacting individuals' perceptions of long-term benefits and economic feasibility. Understanding this heuristic is essential for devising strategies that mitigate these initial biases and encourage more informed and favorable decisions regarding solar energy investments.

3.3.3 Anchoring and Adjustment Heuristic

The anchoring and adjustment heuristic plays a significant role in influencing solar energy adoption decisions. This cognitive bias, as described by Jindal & Shrimali (2022) and Kahneman et al. (1982), refers to the tendency for individuals to over-rely on the first piece of information they receive (the "anchor") when making subsequent judgments or estimations. In the context of solar energy, the initial cost of installation often acts as a powerful anchor, potentially leading to an underestimation of long-term financial benefits and energy savings.

This can discourage individuals from adopting solar energy, even when it may ultimately prove to be a cost-effective investment (Akrofi & Okitasari, 2023).

However, research suggests that this anchoring effect can be mitigated through strategic framing and the provision of comprehensive information. By presenting potential solar adopters with clear and assertive data about the actual payback period and return on investment, their initial perceptions can be adjusted, making them more receptive to the long-term economic advantages of solar energy (Vibrans et al., 2023). Furthermore, framing the cost of solar panels in terms of manageable monthly energy savings or loan repayments, rather than emphasizing the total installation cost, can diminish the impact of the anchor and make the investment appear more feasible and attractive (Kause et al., 2019; Kriechbaum et al., 2023).

The influence of the anchoring and adjustment heuristic is evident in various studies on solar energy adoption. For instance, Bailey et al. (2021) and Bhardwaj et al. (2019) demonstrated that providing clear and detailed information about the long-term financial benefits of solar energy, such as payback periods and return on investment, can significantly influence an individual's attitude by helping individuals adjust their initial cost perceptions. Similarly, Agarwal et al. (2023) highlighted the importance of framing the cost of solar panels in terms of monthly energy savings or loan repayments to reduce the anchoring effect and make solar energy investments more appealing.

The anchoring and adjustment heuristic is also relevant in the context of policy interventions aimed at promoting solar energy adoption. In Brazil, for example, the implementation of Feed-in Tariffs (FiTs) and net metering policies can be seen as a way to establish a positive anchor for the financial benefits of solar energy. By setting a benchmark for the attractiveness of renewable energy generation and allowing solar users to sell excess electricity back to the grid, these policies create a reference point that can shape consumers' expectations and encourage adoption (Garlet et al., 2019; Parker, 2023).

In conclusion, understanding the anchoring and adjustment heuristic is crucial for developing effective strategies to promote solar energy adoption. By recognizing how this cognitive bias can influence perceptions of upfront costs and long-term benefits, policymakers and stakeholders can design targeted interventions to mitigate its negative effects and encourage more informed decision-making.

Hence, we hypothesize that:

H5: The anchoring and adjustment heuristic directly and positively impacts the attitude to adopt solar energy.

Having examined the specific heuristics that can influence attitudes toward solar energy adoption, this section delves into the mediating role of choice heuristics in the relationship between attitude and intention. To understand this dynamic, the research draws upon dual-process theories, which distinguish between intuitive (Type 1) and reflective (Type 2) thought processes. This framework helps illuminate how individuals navigate the complex considerations involved in solar energy adoption, balancing quick, heuristic-driven judgments with more deliberate, analytical evaluations. By exploring this interplay, the study aims to uncover the nuanced ways in which cognitive shortcuts shape intentions and ultimately drive sustainable energy choices

3.3.4 Choice Heuristics

In the domain of sustainable energy adoption, the interplay between intuitive (Type 1) and reflective (Type 2) thought processes emerges as a critical determinant of attitudes and intentions (Evans, 2019). Dual-process theories provide a framework for understanding these cognitive shortcuts. Intuitive thinking is characterized by automaticity, whereas reflective thinking involves conscious reasoning and analytical deliberation (Raue & Scholl, 2018).

Decisions about solar energy adoption often involve complex considerations of costs, benefits, and long-term implications, necessitating reflective System 2 processing. However, intuitive, heuristic-driven thinking (System 1) can also be influential, particularly in the initial stages of decision-making or when individuals face information overload or time constraints (Korteling et al., 2023; Raue & Scholl, 2018). These perspectives on decision-making rationality underscore the importance of considering the interplay between heuristics and analytical thinking in understanding and promoting sustainable energy choices.

Insights from dual-process theories can inform the design of interventions and communication strategies to encourage solar energy adoption. By targeting both intuitive and reflective processes, policymakers and marketers can develop more effective approaches that resonate with individuals' cognitive tendencies and motivate behavior change (Abreu et al., 2019; Rai & Robinson, 2015).

He et al. (2020) studied the comprehension of solar energy labels and the role of heuristic-driven thought in China and the Netherlands. The authors concluded that intuitive "System 1" thinkers rely more on quick heuristics and overall impressions, often influenced by visual elements like colors or letter grades. In contrast, deliberative "System 2" thinkers carefully analyze the information and make calculations, spending more time comparing numerical values on labels. The study's insights are valuable for marketers and policymakers, highlighting the need to tailor solar energy adoption campaigns to different cognitive styles for more effective outcomes.

Theoretical discussions surrounding dual-process theories in the context of solar energy adoption explore various implications for understanding decision-making processes (Fathima et al., 2022). These discussions address the challenges of reconciling intuitive and reflective processes, the role of emotions and social norms in shaping attitudes towards solar energy, and the potential impact of cognitive biases on decision outcomes (Goel, 2024). Dual-process reasoning perspectives elucidate these theoretical underpinnings and provide a framework for understanding individuals' cognitive shortcuts and behaviors regarding solar energy adoption.

Insights from dual-process theories have practical applications in promoting solar energy adoption and sustainability initiatives. In education and outreach endeavors, understanding the interplay between intuitive and reflective processes can inform the design of communication strategies tailored to resonate with diverse audiences (Gosnell & Bazilian, 2021). In policy formulation and program design, insights derived from dual-process theories can steer the development of interventions addressing barriers to solar energy adoption, such as financial constraints or information asymmetry (Korteling et al., 2023).

This section has highlighted the role of choice heuristics in shaping decision-making in the context of solar energy adoption. By examining key concepts, empirical evidence, theoretical implications, and practical applications, we have gained valuable insights into the complexities of individuals' cognitive shortcuts and behaviors regarding sustainable energy choices (Neys, 2023).

Based on this theoretical framework, we hypothesize the following:

H5: Choice heuristics positively predict intention toward solar energy adoption.

H6: Attitude positively predicts choice heuristics.

H7: Choice heuristics mediate the relationship between attitude and intention toward solar energy adoption.

Having explored the dynamic interplay between intuitive and reflective thinking in shaping solar energy adoption decisions, the following section delves into the broader discussion of heuristics, examining contrasting approaches and paradigm interpretations within the field of cognitive psychology. This analysis will provide a deeper understanding of the theoretical foundations and diverse perspectives surrounding the use of heuristics in decision-making, further enriching the context for this study.

3.4 Discussion of Heuristics: Contrasting Approaches and Paradigm Interpretations

The concept of heuristics, as explored by Daniel Kahneman and Gerd Gigerenzer, represents a cornerstone in cognitive psychology, albeit with diverging interpretations. Kahneman's approach, grounded in the heuristics-and-biases program, frames heuristics as cognitive shortcuts that often lead to systematic biases and errors in judgment (Kahneman & Tversky, 1979). This perspective emphasizes the limitations of human rationality, underscoring the tendency of heuristics to deviate from normative standards. For instance, the anchoring heuristic illustrates how initial reference points unduly influence subsequent decisions, often leading to suboptimal outcomes.

Conversely, Gigerenzer's ecological rationality framework argues that heuristics are adaptive strategies that align with the structure of the environment. Far from being inherently flawed, heuristics are viewed as efficient tools for decision-making under uncertainty, particularly in real-world contexts where information is incomplete or time is constrained (Gigerenzer & Goldstein, 1996). This paradigm highlights the functional utility of heuristics, such as the availability heuristic, which leverages easily retrievable information to facilitate quick and effective decisions.

The divergence between Kahneman and Gigerenzer's perspectives can be interpreted through the lenses of Thomas Kuhn's (1962) and Imre Lakatos's (1978) philosophies of science. Kuhn's framework of scientific revolutions offers a lens to view Kahneman's heuristics-and-biases program as the dominant paradigm within cognitive psychology. Gigerenzer's ecological rationality (Mohamad Hjeij & Arnis Vilks, 2023; Tversky & Kahneman, 1974) (2011,2015), represents a competing paradigm, challenging the established narrative by reframing heuristics as adaptive rather than flawed. Kuhn's notion of paradigm shifts underscores the potential for ecological rationality to redefine the field, should its propositions gain wider empirical and theoretical traction (Kuhn, 1962).

Lakatos's (1978) methodology of scientific research programs provides an alternative interpretation. Here, Kahneman's work forms the "core" of a progressive research program, supported by empirical evidence from controlled experiments that validate its claims (Mohamad Hjeij & Arnis Vilks, 2023; Tversky & Kahneman, 1974). Gigerenzer's ecological rationality (Gigerenzer, 2024; Gigerenzer & Goldstein, 1996) could be viewed as a rival research program, characterized by a "protective belt" of hypotheses that extend its core principles to diverse contexts. The evolution of these programs depends on their ability to generate novel predictions and empirical support (Lakatos, 1978).

This ongoing debate has profound implications for sustainability research, particularly in areas like solar energy adoption. Kahneman's framework cautions against potential biases in decision-making, such as overreliance on initial cost estimates (anchoring) or skewed perceptions of risk (availability). In contrast, Gigerenzer's approach advocates leveraging these heuristics to design adaptive decision-making frameworks that resonate with environmental and socio-economic realities (Amos Tversky et al., 1973; Kahneman, 1992; Gigerenzer, 2008). By framing heuristics as contextually efficient tools, ecological rationality offers a complementary lens to enhance behavioral models like the Theory of Planned Behavior (TPB) (Mousavi & Gigerenzer, 2017). This integration enriches the understanding of cognitive processes, providing actionable insights for promoting sustainable behaviors.

3.4 Integration with the Theory of Planned Behavior

Several empirical works have used the Theory of Planned Behavior (TPB) to explain the acceptance of solar energy and photovoltaic systems. For instance, Vu et al. (2023) showed that perceived government incentives, perceived environmental knowledge, and perceived innovativeness positively correlated with adoption intention in Vietnam. In the same region, Huansuriya & Ariyabuddhiphongs (2023) established that economic expectations, attitudes, perceived behavioral control, social norms, and innovativeness positively influenced Thailand's adoption intention.

Tanveer et al. (2021) added perceived risk, perceived self-efficacy, and openness to technology into the TPB framework and confirmed that perceived social norms, self-efficacy, and perceived benefit of solar PV are positively associated with Pakistan's solar PV adoption intention. Waris et al. (2022) also emphasized that publicity information significantly and positively influenced household sign-up for solar energy in Pakistan, with green norms playing a prominent role.

These studies collectively highlight the versatility of the TPB in explaining the various factors that contribute to the adoption of solar energy and photovoltaic systems across diverse contexts. They demonstrate the TPB's ability to incorporate a wide range of variables, including perceived benefits, social norms, self-efficacy, and environmental concerns, to provide a comprehensive understanding of the decision-making process.

4. Method

This chapter presents the methodological procedures adopted in this research. The study aligns with the positivist paradigm, the predominant approach for consumer behavior research since the 1960s (Hunt, 1991). The positivist paradigm emphasizes empirical evidence and quantitative analysis to objectively understand phenomena (Creswell & Creswell, 2018). A quantitative, deductive approach is used, grounded in statistical analysis to test pre-established hypotheses. The Structural Equation Modeling (SEM) method is chosen for its capacity to examine multiple relationships simultaneously and compare various nested models to determine the best fit for the data (Tarka, 2018). SEM is particularly effective for exploring complex relationships in marketing and consumer behavior studies (Matsueda, 2012).

The descriptive research design focuses on observing and describing phenomena without manipulation, aiming to classify, compare, and interpret data to understand specific populations or behaviors (Hair et al., 2013). A literature review was conducted using national and international academic databases, including Periódicos Capes, Science Direct, Scopus, and Google Scholar, incorporating reviewed articles, systematic reviews, and relevant statistical reports to establish a solid theoretical framework. The data collection was finished on 11/14/2024, and the respective analyses were conducted using the software JASP®, version 0.19.1. and 0.19.2

4.1 Data collection and survey development

The research collected primary data through an online structured survey using snowball sampling, following the methodological approach of Hair et al. (2013), between October and November 2024. Recruitment ended on November 14, 2024, and gathered 380 responses. Snowball sampling was chosen for its suitability when appropriate secondary databases are lacking; respondents were recruited through referrals or social networks (Tomáš Došek, 2021).

The surveys guaranteed respondent anonymity in accordance with the Brazilian data protection law (LGPD - Lei 13.709/18); additionally, participants were questioned about their interest in receiving the research results. The questionnaire used a 1-7 Likert scale (Likert, 1932; Hair et al., 2013; Malhotra et al., 2010). Mandatory responses ensured completeness before proceeding to subsequent stages.

The survey was developed in adherence to the standards outlined in the International Test Commission 2nd edition (2017), incorporating the proposed guidelines and an extensive literature review of methodological procedures for quantitative research. These standards ensure the methodological rigor and reliability of the data collected, providing a robust foundation for the analysis. This comprehensive approach to data collection and adherence to international guidelines enhances the credibility and validity of the research findings.

TABLE 1: International Test Guidelines (2017)

Guidelines	Description
1	Obtain necessary permission from the holder of the intellectual property rights.
2	Evaluate overlap in construct definitions across populations.
3	Minimize cultural and linguistic differences irrelevant to the test's use.
4	Consider linguistic, psychological, and cultural differences in translation and adaptation.
5	Use appropriate translation designs and procedures for the intended populations.
6	Ensure test instructions and item content have similar meanings.
7	Collect pilot data for item analysis, reliability, and validity studies.
8	Select a sample with relevant characteristics and sufficient size for analysis.
9	Provide statistical evidence for construct, method, and item equivalence.

Source: International Test Commission

The constructs and items captured aspects of consumer behavior and decision-making processes related to solar energy adoption, such as Intention Toward Solar Energy Adoption (Fazal et al., 2023), Attitude Toward Solar Energy Adoption (Masrahi et al., 2021), Choice heuristics (Darke et al., 2006), and availability, anchoring, and representativeness heuristics (Neenu Chalissery et al., 2023). The adapted items were carefully translated and modified to suit the Brazilian context, ensuring cultural and linguistic appropriateness. The Portuguese adaptation was distributed to gather the necessary data.

A pre-test was conducted to assess the clarity and comprehensibility of the translated and adapted items. Thirty people were asked to evaluate the survey. This first sample comprised 15 master's students and teachers from the Federal University of Pernambuco and 15 people not related to academia but shared characteristics with the target population (i.e., urban residents, 25 years old or older). Few considerations, mostly regarding sentencing appropriateness and readability, were made to enhance the comprehensiveness and suitability of the items. The final adapted items and their respective codes are presented in the table below. The language used in the distributed survey was Portuguese.

Table 2: Adapted survey Items and codes.

Constructs	Adapted Items	Portuguese translation	Code
Intention Toward Solar Energy Adoption "Renewable Energy and Sustainable Development—Investigating Intention and Consumption among Low-Income Households in an Emerging Economy" (Fazal et al. 2023)	You would use solar energy even if the supply was inconsistent.	Você usaria energia solar mesmo se o fornecimento não fosse constante	IT1
	You plan to use more solar energy in the coming years.	Você planeja usar mais energia solar nos próximos anos.	IT2
	You plan to use more solar energy rather than non-renewable energy.	Você está mais disposto a usar energia solar em comparação com outras fontes de energia	IT3
	You would consider the usage of solar energy for ecological motives.	Você considerará o uso de energia solar por razões ecológicas.	IT4
	The likelihood of you starting to use solar energy in the next two years is high.	A probabilidade de você começar a usar energia solar nos próximos 2 anos é alta.	IT5
	You would opt to change to solar energy if you had the choice	Você optaria por mudar para energia solar, se tivesse a escolha.	AT1
	The financial benefits of solar energy use are more important than environmental benefits	Os benefícios financeiros do uso da energia solar são mais importantes do que os benefícios ambientais	AT2

Attitude Toward Solar Energy Adoption “Factors influencing consumers’ behavioral intentions to use renewable energy in the United States residential sector” (Masrahi, Wang, Abudiya, 2021)	I believe that renewable energy is reliable source of electricity	Acredito que a energia renovável é uma fonte confiável de energia	AT3
	Solar energy use helps to decrease the electric energy bill in the long term	Energia solar ajuda a reduzir os custos de energia elétrica a longo prazo	AT4
	Solar energy is a reliable source of electricity	A energia solar é uma fonte confiável de energia.	AT5
	Use solar energy is a correct choice	Usar energia renovável é uma escolha acertada.	AT6
	Do you have interest in learning more about renewable energy	Você tem interesse em aprender mais sobre energia renovável.	AT7
	You support the usage of renewable energy in your community	Você apoia o uso de energia renovável na sua comunidade.	AT8
Choice Heuristics “The Importance and Functional Significance of Affective Cues in Consumer Choice” (Darke, Chattopadhyay, and Ashworth (2006))	Solar energy contributes to the environment preservation	Energia solar contribui para a preservação do meio ambiente	CH1
	The potential installation costs influences your decision to adopt	Os custos potenciais da instalação de energia solar influenciam suas decisões sobre adotá-la	CH2
	The financial savings that solar energy can offer is important to you	A economia financeira potencial que a energia solar pode proporcionar é importante para você	CH3
	You trust on peer recommendations in matters like solar energy adoption	Você confia nas recomendações de pessoas próximas quando se trata de adotar energia solar	CH4
Availability Heuristic, Anchoring and Adjustment Heuristic, and Representativeness Heuristic “Does the Investor’s Trading Experience Reduce Susceptibility to	Negative news would you opt to delay your plans to adopt solar energy	Notícias negativas fariam você adiar a adoção de energia solar.	AA1
	Upfront installation costs are considered but for you, long term savings are as important when deciding to adopt solar energy	Você considera o custo inicial da instalação, mas a economia a longo prazo também é importante na sua decisão de adotar energia solar.	AA2

Heuristic-Driven Biases? The Moderating Role of Personality Traits” (Neenu Chalissery et al., 2023)	You compare your current electricity bill to the solar energy benefits when deciding to adopt it	Você compara os custos de eletricidade com os benefícios da energia solar ao tomar decisões sobre adotá-la.	AA3
	A consistent increase on your electricity bill augments the probability for you to adopt solar energy	Um aumento consistente na sua conta de eletricidade aumenta sua probabilidade de adotar energia solar.	AA4
	You are concerned about the environmental impact of your electricity consumption.	Você se preocupa com o impacto ambiental do seu consumo de energia.	AV1
	You make an effort to understand every aspect of your electricity bill.	Você se esforça para entender todos os detalhes da sua conta de energia.	AV2
	Positive evaluations from your peers would enhance the probability of adopting solar energy	Avaliações positivas de colegas aumentam sua probabilidade de adotar energia solar.	AV3
	Frequent media coverage about solar energy would enhance your disposition of adopting solar energy	Discussões frequentes na mídia sobre energia aumentam sua disposição em adotar energia solar.	AV4
	I would consider installing solar energy if I knew people who have a similar lifestyle implemented with success	Eu consideraria instalar energia solar se conhecesse pessoas em situação semelhante à minha que fizeram isso com sucesso.	RP1
	I believe solar energy would fit well for me because other people with similar lifestyle as mine had a succeed with it	Eu acredito que a energia solar funcionaria bem para mim porque pessoas com estilo de vida semelhantes tiveram sucesso com ela.	RP2
	I believe my current energy provider will keep its quality	Eu acredito que meu atual provedor de energia manterá a	RP3

	standards, because people with similar lifestyle as mine had positive experiences with it.	qualidade do serviço, pois pessoas com estilo de vida semelhante ao meu têm experiências positivas com ele.	
	I would avoid adopting solar energy if the people with whom I am identified with had bad experience in it	Eu evitaria adotar energia solar se pessoas com quem me identifico tivessem tido uma má experiência com ela.	RP4

5. Introduction to the results' analysis

This chapter presents the methodological procedures adopted in this research. The study aligned with the positivist paradigm, the predominant approach for consumer behavior research since the 1960s (Hunt, 1991). The positivist paradigm emphasizes empirical evidence and quantitative analysis to objectively understand phenomena (Creswell & Creswell, 2018). A quantitative, deductive approach was used, grounded in statistical analysis to test pre-established hypotheses. Structural Equation Modeling (SEM) was chosen for its capacity to examine multiple relationships simultaneously and compare various nested models to determine the best fit for the data (Tarka, 2018). SEM is particularly effective for exploring complex relationships in marketing and consumer behavior studies (Matsueda, 2012).

The descriptive research design focused on observing and describing phenomena without manipulation, aiming to classify, compare, and interpret data to understand specific populations or behaviors (Hair et al., 2013). A literature review was conducted using national and international academic databases, including Periódicos Capes, Science Direct, Scopus, and Google Scholar, incorporating reviewed articles, systematic reviews, and relevant statistical reports to establish a solid theoretical framework. The data collection was completed on November 14, 2024, and the respective analyses were conducted using the software JASP®, versions 0.19.1 and 0.19.2.

5.1 Sample Composition

Descriptive analysis provides an overview of the respondents' characteristics, relevant for identifying sample idiosyncrasies. Respondents were approached via social media and email campaigns (Malhotra, 2010; Došek, 2021). The final dataset comprised 380 respondents, predominantly from the Northeastern region (74.1%). The gender distribution was relatively balanced, with 52.6% identifying as female. The generational composition shows that Millennials (49.5%), Gen X (23.7%), and Gen Z (21%) collectively accounted for 93.9% of respondents. These groups are often associated with higher engagement in technology and sustainability practices (Lacroix & Jolibert, 2015). However, the limited representation of Baby Boomers (5.8%) may restrict the study's ability to examine adoption barriers faced by older generations, who may have greater economic resources and distinct attitudes toward solar energy.

In terms of educational attainment, 77.7% of respondents reported holding an undergraduate degree or higher, while only 6.8% did not have a university degree. This high level of education is consistent with the study's focus on middle-to-high income urban households, likely to engage in energy decision-making. Income distribution reveals that 62% of participants reported monthly earnings between R$3,636.00 and R$18,180.00, reflecting a sample of economically stable individuals more capable of affording the initial investment required for solar energy systems.

Concerning the families' composition and marital status, 48% reported being married or in a cohabiting relationship, and 47% reported being single. Only 0.3% reported being divorced, and 0.08% reported being widowed. The family sizes ranged from 1 (0.08%) to 7 family members (0.3%), the vast majority reported having a family composed of 2, 3, and 4 members (respectively 28.9%, 29.7%, and 21.6%). These findings reflect the diversity of family structures, which could influence energy consumption patterns and decision-making processes related to solar energy adoption.

In summary, the sample reflects a predominantly younger, educated, and economically stable population, largely from the Northeastern region of Brazil. A slight majority of respondents identify as female. Millennials, Gen X, and Gen Z make up the vast majority of the sample, with limited representation from Baby Boomers. Most respondents hold an undergraduate degree or higher and report monthly earnings within a middle-to-high income bracket. Family structures are diverse, with a near-even split between those married or cohabiting and single individuals. Family sizes predominantly range from 2 to 4 members. While this demographic profile suggests a population likely to engage with sustainability initiatives, the underrepresentation of older generations and less affluent individuals should be considered when interpreting the results.

5.1.1 Constructs Descriptive statistics

The descriptive statistics provide an overview of the construct's responses used in the study, highlighting the central tendencies, variability, and overall distribution characteristics. According to (J. F. Hair et al., 2013), descriptive statistics offer insights into the data's quality, distribution, and potential anomalies. By examining the mean, standard deviation, skewness, and kurtosis of each construct, and assess the dataset normality through the Shapiro Wilk test, researchers can assess the general trends and identify any non-normality or extreme values that could affect the statistical analysis (Cooksey, 2020). This analysis serves as a prerequisite for evaluating the measurement model, allowing researchers to interpret the nature of the constructs before advancing to more complex modeling steps, the normality histograms and tables are located in the appendix B.

The availability heuristic construct, reflecting the reliance on easily accessible and memorable information, exhibited mean scores ranging from 4.05 to 6.20 across items, suggesting a moderate tendency to use availability as a cognitive shortcut. Standard deviations ranged between 1.06 and 1.93, indicating variability in responses, particularly on some items. Negative skewness values (-0.17 to -1.73) suggest that respondents leaned slightly toward higher agreement with these items, while kurtosis values (-1.13 to 3.53) highlight diverse patterns of distribution sharpness. The Shapiro-Wilk test confirmed non-normality in all items, a common characteristic in behavioral data. These findings indicate that the availability heuristic plays a varied yet notable role in shaping respondents' perceptions and attitudes.

The anchoring and adjustment heuristic, which captures how individuals use initial reference points to form subsequent judgments (Grimm, 2010), showed mean scores between 4.05 and 6.20, similar to the availability heuristic. Standard deviations ranged from 1.06 to 1.93, reflecting moderate variability in responses. Negative skewness values (-0.17 to -1.73) indicate a tendency toward higher agreement, while kurtosis values (-1.13 to 3.53) suggest mixed distribution patterns, with some items exhibiting sharp peaks. Shapiro-Wilk results also indicated non-normality. These results emphasize the influence of anchoring in respondents' decision-making processes, particularly in shaping initial impressions of solar energy.

The representativeness heuristic, reflecting the tendency to associate solar energy with familiar or stereotypical characteristics, had mean scores ranging from 4.42 to 5.87, suggesting a generally favorable perception of representativeness. Standard deviations (1.53 to 1.94) were moderate, indicating consistent response patterns across items. Skewness values (-1.11 to -0.27) reveal a slight preference for higher agreement, while kurtosis values (-0.98 to 2.04) suggest relatively flat or balanced distributions. The Shapiro-Wilk test confirmed non-normality. These results highlight the representativeness heuristic as an influential factor in forming positive perceptions of solar energy, particularly through associations with sustainability and modernity.

The choice heuristic construct, capturing the role of simplicity in decision-making, had high mean scores (6.02 to 6.29), reflecting strong agreement across all items. Low standard deviations (1.07 to 1.29) suggest high consistency in responses. Strong negative skewness values (-1.53 to -1.92) show a pronounced tendency toward higher scores, while kurtosis values (2.30 to 4.25) indicate sharper peaks. Shapiro-Wilk results confirmed non-normality. These findings demonstrate that respondents strongly value simplicity in the solar energy decision-making process, underscoring the importance of reducing complexity in marketing and policy communication.

The attitude construct, representing respondents' overall perceptions of solar energy adoption, displayed wide-ranging mean scores (3.65 to 6.81), suggesting diverse attitudinal perspectives. Standard deviations ranged from 0.68 to 1.82, highlighting variability across items. Negative skewness values (-4.88 to -1.26) indicate a strong tendency toward higher agreement for most items, while kurtosis values varied significantly (-0.81 to 27.87), with some items showing extreme peaks. Shapiro-Wilk results confirmed non-normality. These findings suggest that attitudes toward solar energy are generally positive, with certain dimensions (e.g., environmental benefits) resonating more strongly among respondents.

The intention construct, which measures respondents' willingness to adopt solar energy, had mean scores ranging from 4.58 to 6.11, reflecting moderately strong intentions overall. Standard deviations (1.25 to 2.03) suggest some variability in responses, while skewness values (-1.18 to -0.37) indicate a mild tendency for higher scores. Kurtosis values (-1.00 to 2.53) reflect relatively balanced distributions. Shapiro-Wilk results confirmed non-normality. These findings suggest that respondents exhibit moderately strong intentions to adopt solar energy, though individual differences highlight varying levels of readiness and motivation.

Across all constructs, responses generally indicate a positive orientation toward solar energy adoption. The choice heuristic showed the strongest agreement, with high means and low variability, underscoring the importance of simplicity in decision-making. Constructs like availability and anchoring heuristics revealed moderate agreement but greater variability, highlighting individual differences in reliance on cognitive shortcuts. Representativeness heuristics consistently elicited favorable responses, likely due to associations with positive stereotypes like sustainability. Attitudes were predominantly positive, with some items showing extremely high agreement, suggesting that certain aspects of solar energy (e.g., environmental benefits) resonate strongly with respondents. Intentions to adopt solar energy were moderately strong, though variability across items suggests differing levels of readiness. Overall, these patterns reflect a sample that is generally receptive to solar energy but exhibits nuanced differences in how heuristics and attitudes influence their decision-making.

Given the attested the non-normality among the majority of the respondents, the method of Partial Least Squared Structural Equation Modeling was chosen in detriment to Co-variance based Modeling approach, besides the Shappiro-Wilk test of normality, the Mahalanobis distance test was performed 2 times in order to identify and delete outliers from the dataset. Even though the tests identified over 240 potentially outliers, the deletion proved insufficient to significantly improve the normality of the dataset, hence, the outliers were not accurately identified.

Therefore, it is an indication that the sample is highly heterogenous, which is expected in research that have employed the snowball technique and are vulnerable to social desirability bias, these findings aligns with the works of Grimm (2010) and Durmaz et al., (2022), they discussed how self-reported surveys related to politics and environmental issues are more susceptible to this kind of sampling bias.

5.1.2 Common method bias and multicollinearity assessment

Assessing multicollinearity is a critical statistical step in PLS-SEM analysis, as it evaluates whether the latent variables are being interpreted as intended and whether shared variance compromises the validity of the constructs. As Kock (2015) explains: “Common method bias, in the context of PLS-SEM, is a phenomenon caused by the measurement method used in an SEM study, rather than the network of causes and effects in the model being studied.”

If unchecked, common method bias can undermine construct reliability by introducing high multicollinearity, making predictor variables appear redundant. To address this, the

Variance Inflation Factor (VIF) is a key diagnostic tool. VIF values help determine whether multicollinearity among items is problematic, signaling the need for model adjustments. According to Kock (2015), a VIF threshold of 3.3 is recommended for PLS-SEM analyses. Values exceeding this threshold indicate excessive shared variance between constructs, necessitating refinements in the model. Incorporating VIF diagnostics ensures statistical robustness, particularly in applied fields such as marketing, management, and behavioral studies.

The primary objective of VIF analysis is to detect multicollinearity, while other reliability tests focus on internal consistency. By identifying redundant overlap among variables, VIF enhances the reliability of path coefficients and the overall robustness of the model. It complements other reliability measures such as Cronbach’s alpha to provide a comprehensive evaluation of the model's integrity.

In this study, the JASP software, leveraging the LAVAAN package for R, was used to run the PLS-SEM analysis. Coding the measurement and structural models was required, and iterative refinements were conducted to achieve optimal model indices. Each model iteration was evaluated based on item loadings and their respective VIF values. The syntax used and the outputs for each model are presented in the appendix. The VIF results are summarized in the following table:

Table 3: Variance inflation factor across models.

	Availability	Representativeness	Anchoring and adjustment	Choice Heuristic	Attitude
Model 1	4.003	4.159	6,299	5,789	2,911
Model 2	4.002	2.588	3.105	3.967	3.071
Model 3	4.001	2.263	3.092	3.912	3.395
Model 4	2.789	2.570	2.229	3.350	3.350

Source: Author (2024)

For most of the variables the refinements resulted in significant improvements in the VIF except for the constructs Choice Heuristic and Attitude toward solar energy, their score indicates a redundancy among the constructs. More details about the refinements will be presented in the upcoming topics.

5.2 Measurement model assessment

A Confirmatory Factor Analysis (CFA) was conducted to assess the unidimensional structure of the measurement model, enhancing its reliability and validity. Initially, the Maximum Likelihood (ML) estimator yielded inadequate fit indices, prompting exploration of alternative methods: Unweighted Least Squares (ULS) and Robust Diagonally Weighted Least Squares (RDWLS). This decision was guided by methodological recommendations from Li (2016) and Savalei (2021), who demonstrated the suitability of ULS and DWLS for non-normal data through rigorous statistical comparisons. Furthermore, Kline (2016, pg 461) recommends not retaining a model solely on model fit indices and advises to deal with care with non-continuous data through exploring more an estimation method better aligned to the dataset's profile.

Following Hair et al., (2018) guidelines, the research provides credible measurement frameworks by: (1) achieving high internal consistency (CR), (2) confirming convergent validity through strong loadings and Average Variance Extracted (AVE), and (3) demonstrating discriminant validity using Fornell-Larcker and Heterotrait-Monotrait Ratio (HTMT) criteria. A well-grounded measurement model enables accurate testing and interpretation of structural relationships within the SEM.

The first analysis (Model 1) utilized the ML estimator, including all 29 items in the measurement model. The results showed very poor model fit, with $\chi^2/df = 5.92$, CFI = 0.765, TLI = 0.737, RMSEA = 0.114, and SRMR = 0.070. These results remained unsatisfactory even after the removal of low-loading items, indicating that the estimator's assumptions did not align with the dataset's characteristics. This outcome raised concerns about the suitability of ML for this study and prompted the use of ULS and RDWLS, which are specifically designed for categorical and non-normal data.

The second analysis (Model 2) employed the ULS estimator, which is better suited to categorical data and less sensitive to model misspecifications (Shi & Maydeu-Olivares, 2020). Refinements were made following Hair et al. (2018) guidelines for item removal after its qualitative assessment: items with loadings below 0.40 were deleted, while items between 0.40 and 0.50 were evaluated for their contributions to reliability and validity. Stronger loadings (≥ 0.50) were prioritized for retention. The following items were deleted during this phase: AV2 (0.522), AA1 (-0.089), RP4 (0.109), CH2 (0.071), AT2 (0.084), AT3 (0.20), IT2 (1.331), and IT5 (1.415). These deletions resulted in significant improvements to model fit, achieving $\chi^2/df = 5.12$, CFI = 0.954, TLI = 0.945, RMSEA = 0.114, and SRMR = 0.065. However, while the results were much better than those obtained with the ML estimator, the RMSEA value remained above the recommended threshold of 0.08.

The third analysis (Model 3) utilized the RDWLS estimator, which is also suitable for non-normal, ordinal datasets and is recommended for sample sizes of $N \leq 500$ (DiStefano & Morgan, 2014; Li, 2016). Additional refinements were made to further improve the model, leading to the deletion of AT7 (0.502), AT8 (0,400), IT1 (0.696), and IT4 (0.417). These items were removed due to theoretically grounded exclusion to achieve the best fit model possible, as prescribed by Hair et *al*., (2018), a third CFA refinement would include the deletion of <0,7 factor loadings.

Furthermore, the Choice Heuristic construct was excluded due to persistent issues, such as low AVE (< 0.50) and weak factor loadings across all estimation methods. The exclusion of this construct not only improved model fit but also enhanced the parsimony of the model. The final fit indices demonstrated excellent model performance, with χ^2/df = 2.97, CFI = 0.994, TLI = 0.992, RMSEA = 0.019, and SRMR = 0.066. The fit indices across all three models are summarized in the table below:

Table 4: Model fit indices

Index	Threshold*	Model 1 (ML)	Model 2 (ULS)	Model 3 (DWLS)
CFI	≥ 0.90	0.765	0.954	0.994
TLI	≥ 0.90	0.737	0.945	0.992
RMSEA	> 0.08	0.114	0.114	0.019
SRMR	≤ 0.08	0.070	0.065	0.066
Chi-Square/df	≤ 3.0	5.92	5.12	2.97

*Treshold values for model fit (HAIR *et al*, 2018)
Source: Author (2024)

The poor performance of the ML estimator highlighted its limitations in handling non-normal categorical data, reinforcing the need for estimators such as Robust ULS and DWLS. While ULS produced significant improvements, the RDWLS estimator provided the best fit indices and aligned more closely with the dataset's characteristics. It is noteworthy, however, that achieving this level of model performance required the exclusion of an entire construct (Choice Heuristic), and several items, under the estimation of Maximum Likelihood and Unrestricted Least Squares. This exclusion raised concerns about the theoretical contribution of the final model.

Although statistical parsimony is important, it must be balanced with theoretical completeness (Hair et al.,2017; Rigdon, 2012). To address this, future evaluations should incorporate a holistic approach, combining model fit indices with convergent and discriminant validity, reliability measures, and predictive relevance metrics such as Q^2 and F^2. In conclusion, the RDWLS-based model demonstrated superior empirical performance and robustness for the given dataset, providing a strong foundation for subsequent structural modeling. However, the exclusion of problematic constructs and items underscores the importance of reconciling theoretical and empirical considerations in measurement model refinement.

Table 5: Measurement model 2 factor loadings

MODEL 2 Robust ULS ESTIMATOR								
Factor loadings								
AVAILABILITY	AV1	0.712						
	AV3	0.977						
	AV4	1.100						
ANCHORING AND ADJUSTMENT	AA2		0.722					
	AA3		0.734					
	AA4		0.878					
REPRESENTATIVENESS	RP1			1.043				
	RP2			1.538				
	RP3			0.772				
CHOICE HEURISTICS	CH3				0.528			
	CH4				0.747			
ATTITUDE	AT1					0.600		
	AT4					0.496		
	AT5					0.507		
	AT6					0.804		
	AT8					0.489		
	AT7					0.767		
INTENTION	IT2						1.080	
	IT3						0.910	
	IT4						0.846	

Source: Author (2024) NOTE: all p-values are < 0,05

Table 6: Measurement model 3 factor loadings

MODEL 2 Robust DWLS ESTIMATOR							
Factor loadings							
AVAILABILITY	AV1	0.687					
	AV3	0.984					
	AV4	1.096					
ANCHORING AND ADJUSTMENT	AA2		0.740				
	AA3		0.723				
	AA4		0.879				
REPRESENTATIVENESS	RP1			1.081			
	RP2			1.564			
	RP3			0.713			
ATTITUDE	AT1				0.827		
	AT4				0.479		
	AT5				0.762		
	AT6				0.588		
INTENTION	IT2					1.096	
	IT3					0.922	
	IT4					0.823	

Source: Author (2024) NOTE: all p-values are < 0,05

5.2.1 Convergent Validity

The assessment of the internal consistency and the convergent validity are presented at the table 7. For each construct were calculated the Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE), the indices are relevant to evaluate the extent to which the items are related with a given construct (Kline, 2016; Valentini & Damásio, 2016).

Associated, these metrics provide a model's quality evaluation. The main guidelines for these metrics are: Cronbach Alpha's and CR scores > 0,7, to indicate satisfactory performance and AVE of > 0,5 (Hair et al., 2018; Kline, 2016; Hoyle et al., 2013). Given the characteristics of the dataset and research specifications are more tolerant for lower AVE if the CR yields good scores, that are > 0,7 , accordance with (Fornell & Larcker, 1981; J. Hair et al., 2017).

Table 7: Convergent Validity Scores

Construct	Cronbach 's α (Model 2-ULS)	Cronbach 's α (Model 3-DWLS)	CR (Model 2 - ULS)	CR (Model 3 - DWLS)	AVE (Model 2 - ULS)	AVE (Model 3 - DWLS)
Availability	0.689	0.689	0.959	0.954	0.441	0.446
Anchoring & Adj.	0.712	0.712	0.823	0.826	0.454	0.453
Representativeness	0.685	0.719	0.873	0.876	0.478	0.476
Choice Heuristics	0.443		0.615		0.210	
Attitude	0.808	0.801	0.815	0.818	0.513	0.514
Intention	0.672	0.672	0.935	0.936	0.359	0.362

Discriminant validity ensures that constructs are distinct from one another. Hair Jr. et al. 2018) highlight the importance of confirming that each latent factor captures phenomena not represented by other factors in the model. Hence, the Fornell-Larcker criterion is a mean to assess the discriminant validity, the rationale behind the test is that a construct's AVE should be greater than its squared correlation with any other factor (Fornell & Larcker, 1981), indicating that the construct shares more variance with its own indicators than with those of other constructs. For discriminant validity, the diagonal values (square root of AVE) should be greater than the corresponding off-diagonal correlations in the same row and column.

The Heterotrait-Monotrait (HTMT) ratio, was proposed by Henseler et al., 2015, with the purpose of also measuring the discriminant validity of latent variables, assessing the degree of similarity between constructs by examining correlations across and within constructs. HTMT values close to 1 indicate significant overlap between constructs, thus, lower values are preferable. Henseler et al., (2015), proposed a threshold of HTMT ≤ 0.85 to ensure that the construct is not overlapped by others in the model.

While the Fornell-Lacker criterion focuses on comparing the variance explained by a construct in its own indicators versus its correlations with other constructs. It ensures that constructs explain more of their indicators' variance than they share with others. The HTMT criterion directly measures the extent to which two or more constructs are distinct by comparing cross-construct correlations with within-construct correlations (J. F. Hair et al., 2018; Hamid et al., 2017). The results from both tests are presented in the following tables and 9 and further analyzed in the subsequent paragraph.

Table 8: Fornell Lacker Criterion model 2

FORNELL-LACKER CRITERION MODEL 2 ROBUST ULS						
Construct	**Availability**	**Anchoring & Adjustment**	**Representativeness**	**Choice Heuristics**	**Attitude**	**Intention**
Availability	**0.664**	0.420	0.350	0.230	0.300	0.520
Anchoring & Adj.	0.420	**0.674**	0.520	0.400	0.340	0.300
Representativeness	0.350	0.520	**0.691**	0.380	0.270	0.330
Choice Heuristics	0.230	0.400	0.380	**0.458**	0.370	0.300
Attitude	0.300	0.340	0.270	0.370	**0.716**	0.250
Intention	0.520	0.300	0.330	0.300	0.250	**0.599**

Table 9: Fornell Lacker Criterion model 3

FORNELL-LACKER CRITERION MODEL 3 ROBUST DWLS					
Construct	**Availability**	**Anchoring & Adjustment**	**Representativeness**	**Attitude**	**Intention**
Availability	**0.669**	0.300	0.250	0.200	0.350
Anchoring & Adj.	0.300	**0.674**	0.320	0.290	0.280
Representativeness	0.250	0.320	**0.684**	0.300	0.340
Attitude	0.200	0.290	0.300	**0.717**	0.330
Intention	0.350	0.280	0.340	0.330	**0.644**

The Fornell-Larcker Criterion results for Model 2 (ULS) and Model 3 (DWLS) provide an overview of the discriminant validity of constructs in both measurement models. The diagonal values in bold represent the square root of the Average Variance Extracted (AVE) for each construct, while off-diagonal values represent the inter-construct correlations. For discriminant validity to be established, the diagonal values must be greater than the correlations in the same row and column. In Model 2 (ULS), the constructs such as Availability, Anchoring & Adjustment, and Representativeness satisfy discriminant validity criteria as their diagonal values are consistently higher than the off-diagonal correlations. However, Choice Heuristics shows weaker results, with a square root of AVE (0.458) close to some inter-construct correlations, such as with Attitude (0.370) and Representativeness (0.380). Thus, reinforcing the problematic performance of the construct within the model.

In Model 3 (DWLS), a slight improvement in discriminant validity can be observed, particularly for constructs like Availability (square root of AVE: 0.669) and Attitude (0.717), which maintain a larger margin over inter-construct correlations compared to Model 2. The elimination or adjustment of problematic indicators likely contributed to this improvement on the constructs such as Intention and Representativeness also show marginally better performance in maintaining discriminant validity in Model

Table 10: Model 2 HTMT table

Heterotrait-monotrait ratio Model 2 ROBUST ULS					
AVAILABILITY	ANCHORING AND ADJUSTMENT	REPRESENTATIVENESS	CHOICE HEURISTICS	ATTITUDE	INTENTION
1.000					
0.634	1.000				
0.585	0.518	1.000			
0.784	0.850	0.498	1.000		
0.674	0.521	0.319	0.838	1.000	
0.804	0.477	0.482	0.815	0.750	1.000

Table 11: Model 3 HTMT table

Heterotrait-monotrait ratio Model 3 ROBUST DWLS				
AVAILABILITY	ANCHORING AND ADJUSTMENT	REPRESENTATIVENESS	ATTITUDE	INTENTION
1.000				
0.634	1.000			
0.696	0.663	1.000		
0.664	0.521	0.438	1.000	
0.804	0.477	0.497	0.780	1.000

The HTMT results for Model 2 (ULS) demonstrate that most construct pairs exhibit acceptable discriminant validity, with HTMT values below the conservative threshold of 0.85 (Henseler et al., 2015). However, one critical issue arises between Anchoring and Adjustment and Representativeness, which shows an HTMT value of 0.850, precisely at the threshold. This suggests potential conceptual overlap or shared measurement items between these constructs. Furthermore, Choice Heuristics displays marginal HTMT values with other constructs, such as

Attitude (0.815) and Intention (0.838), which approach the upper threshold, indicating these constructs had some degree of redundancy within its measures

The HTMT results for Model 3 (DWLS) show significant improvements in discriminant validity compared to Model 2 (ULS), with all HTMT values falling below the threshold of 0.85. Notably, the HTMT value for Anchoring and Adjustment - Representativeness decreased from 0.850 in Model 2 to 0.663 in Model 3. This improvement highlights the model's refinements to address construct overlaps by deleting items with low factor loadings. Additionally, pairs such as Availability - Representativeness (0.696) and Attitude - Intention (0.780) remain within acceptable ranges, confirming the robustness of Model 3. The removal of Choice Heuristics further eliminates marginal validity issues present in Model 2, making Model 3 the preferred option for analysis due to enhanced discriminant validity and parsimony. These findings support the use of HTMT as a more reliable tool for discriminant validity assessment and affirm the superiority of Model 3 for further analysis and reporting.

Reliability was rigorously evaluated through Composite Reliability (CR), Cronbach's Alpha, and factor loading evaluation to ensure that the constructs and their indicators consistently measured their underlying concepts. Constructs such as Availability, Attitude, and Intention demonstrated strong reliability, with CR values exceeding 0.70 and factor loadings above the acceptable threshold of 0.70, confirming their internal consistency and reliability. In contrast, Choice Heuristics failed to meet the required reliability criteria, exhibiting low CR and Cronbach's Alpha, as well as multiple indicators with weak factor loadings below 0.40. As a result, this construct was excluded in Model 3, significantly improving the overall reliability of the measurement model. This comprehensive reliability assessment ensures that the constructs retained for the structural model analysis are robust, consistent, and reliable, providing a solid foundation for hypothesis testing and further interpretation.

5.3 Structural model assessment

This research employs Partial Least Squares Structural Equation Modeling (PLS-SEM) During the measurement model assessment, the Choice Heuristics construct demonstrated poor reliability and validity. Confirmatory Factor Analysis (CFA) revealed low factor loadings and inadequate Average Variance Extracted (AVE), which persisted across multiple estimation methods (ML, ULS, RDWLS). These findings highlighted significant challenges in operationalizing Choice Heuristics within the structural model. The exclusion of the Choice Heuristic construct significantly improved the model fit indices, in the CFA stage:

- CFI increased from 0.954 (Model 2) to 0.994 (Model 3).
- RMSEA decreased from 0.114 to 0.019.

While the removal enhanced the parsimony and robustness of the structural model, this decision was guided by statistical considerations rather than the theoretical irrelevance of the construct. Therefore, the theoretical role of Choice Heuristics is preserved and explored separately.

To address the theoretical significance of Choice Heuristics, a supplementary mediation analysis is included as an exploratory subtopic. This analysis examines the mediating role of Choice Heuristics in the relationship between attitudes and the intention to adopt solar energy. The following hypotheses are tested:

H5: Attitude positively influences choice heuristic.

H6: Choice heuristic positively influences intention toward solar energy adoption.

H7: Choice heuristic mediates the relationship between attitude and intention toward solar energy adoption.

Choice Heuristics bridge intuitive and reflective cognitive processes, making them a theoretically significant factor in understanding solar energy adoption. Their exclusion from the structural model does not diminish their importance in shaping consumer decision-making. The mediation analysis is conducted separately to isolate the influence of Choice Heuristic without compromising the statistical rigor of the structural model. A bootstrapping approach is used to test the significance of indirect effects, ensuring robust inferences.

TABLE 12: Path Coefficients, Effect Sizes (f^2), Variance Explained (R^2), and Predictive Relevance (Q^2).

Outcome	Predictor	Estimate	Std. Error	p-value	f^2	R^2	Q^2	VIF
ATTITUDE	AVAILABILITY	0.614	0.148	1.786×10^{-5}	0.272			2.412
	ANCHORING AND ADJUSTMENT	0.185	0.129	0.076	0.025	0.447	0.138	1.963
	REPRESENTATIVENESS	-0.069	0.115	0.195	0.007			1.917
INTENTION	ATTITUDE	0.800	0.046	1.169×10^{-66}	1.721	0.632	0.162	

As the reliability and validity concerns of Choice Heuristics were identified, the mediation analysis is presented as exploratory, offering preliminary insights and guiding future research. The combined approach allows the research to retain both empirical rigor and theoretical depth. The refined structural model ensures robust statistical outcomes and interpretable results. The supplementary mediation analysis highlights the nuanced role of Choice Heuristic, contributing to the broader understanding of heuristics in decision-making.

5.3.1 Hypothesis test results

TABLE 13: HYPOTESIS TEST SUMMARY

Hypothesis	Result	Path Coefficient	P-Value	Interpretation
STRUCTURAL MODEL HIPOTESIS TEST RESULTS				
H1: Attitude positively influences intention toward solar energy adoption.	Supported	0.800	$p < 0.05$	Strong positive relationship: attitudes significantly influence intentions.
H2: The availability heuristic positively influences attitudes toward solar energy adoption.	Supported	0.614	$p < 0.05$	Moderately strong positive influence: availability promotes favorable attitudes.
H3: The anchoring and adjustment heuristic positively influences attitudes toward solar energy adoption.	Marginal Support	0.185	$p=0.07$	Weak positive effect: anchoring's role is limited but slightly significant.
H4: The representativeness heuristic positively influences attitudes toward solar energy adoption.	Unsupported	-0.069	$p =0.295$	No significant effect: potential misalignment between mental prototypes and solar.
MEDIATION ANALISYS				
H5: Attitude positively influences choice heuristics.	Supported	0.480	$p < 0.001$	Attitudes positively influence choice heuristics.
H6: Choice heuristics positively influence intention toward solar energy adoption.	Supported	0.118	$p = 0.044$	Weak but significant positive effect of choice heuristics on intentions.
H7: Choice heuristics mediate the relationship between attitude and intention toward solar energy adoption.	Marginal Support	Indirect: 0.056	$p = 0.045$ (indirect)	Mediation is significant; choice heuristics partially mediate the effect of attitude on intention.

H1 was supported ($\beta = 0.800$, $p < 0.05$), indicating that attitude significantly and positively influenced intention toward solar energy adoption. The effect size ($f^2 = 1.721$) suggests a large effect, emphasizing that attitude is the dominant predictor of intention. The variance explained ($R^2 = 0.632$) highlights that attitude accounted for 63.2% of the variation in intention, demonstrating the substantial explanatory power of the TPB model in predicting adoption behavior. Moreover, the predictive relevance ($Q^2 = 0.162$) indicates that attitude meaningfully contributed to the predictive accuracy of the model, further validating its central role in shaping intentions.

H2 was supported ($\beta = 0.614$, $p < 0.05$), suggesting that the availability heuristic had a strong positive effect on attitudes toward solar energy adoption (Hair et al., 2011). The effect size ($f^2 = 0.272$) indicates a medium effect, underlining the importance of vivid and relatable examples in shaping attitudes. The variance explained ($R^2 = 0.447$) shows that 44.7% of the variation in attitudes was accounted for by the model, signifying the availability heuristic's practical relevance in influencing perceptions. Furthermore, the predictive relevance ($Q^2 = 0.138$) highlights that availability contributes meaningfully to the model's predictive power, making it a valuable cognitive shortcut for simplifying decision-making.

H3 received marginal support ($\beta = 0.185$, $p = 0.07$), indicating a weak but positive influence of the anchoring and adjustment heuristic on attitudes. The effect size ($f^2 = 0.025$) reflects a small effect, suggesting that while anchoring has limited impact, it still plays a role in shaping attitudes when comparative cost-benefit information is presented. The variance explained ($R^2 = 0.447$) confirms that the anchoring heuristic contributes to the overall explanatory power of the model for attitudes. Additionally, the predictive relevance ($Q^2 = 0.138$) underscores that this heuristic adds some value to the model's ability to predict attitudes, despite its weaker influence relative to availability.

H4 was not supported ($\beta = -0.69$, $p = 0.295$), showing a non-significant and slightly negative relationship between the representativeness heuristic and attitude. The effect size ($f^2 = 0.004$) reflects a negligible effect, indicating that the representativeness heuristic did not meaningfully contribute to explaining attitudes. However, the variance explained ($R^2 = 0.447$) confirms the overall robustness of the model for predicting attitudes, despite the heuristic's weak performance. The predictive relevance ($Q^2 = 0.138$) highlights that improvements in messaging strategies could enhance this heuristic's role in the future by aligning consumer prototypes with tangible solar energy benefits.

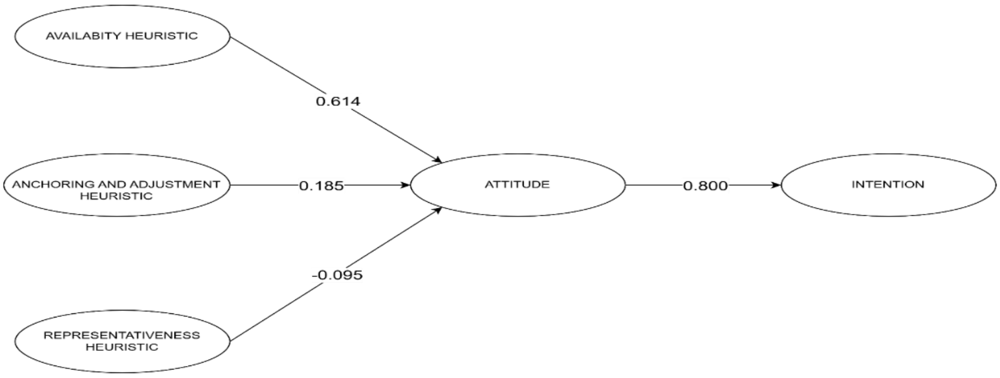
Overall, the results highlighted the substantial contributions of the TPB model and heuristics to predicting solar energy adoption. Attitude (H1) emerged as the strongest predictor of intention ($\beta = 0.800$, $f^2 = 1.721$, $R^2 = 0.632$), demonstrating its dominant role and large explanatory power. The availability heuristic (H2) showed a moderately strong effect ($\beta = 0.614$, $f^2 = 0.272$, $R^2 = 0.447$), reinforcing the importance of accessible and relatable information in shaping attitudes. The anchoring heuristic (H3) made a weaker but notable contribution ($\beta = 0.185$, $f^2 = 0.025$), while the representativeness heuristic (H4) had a negligible effect ($\beta = -0.095$, $f^2 = 0.004$).

The high variance explained for intention ($R^2 = 0.632$) and attitudes ($R^2 = 0.447$) underscores the robustness of the TPB framework in predicting adoption behavior. Furthermore, the predictive relevance values ($Q^2 = 0.162$ for intention and 0.138 for attitudes) confirm the model's ability to deliver meaningful predictions. These findings provide critical insights into how cognitive heuristics interact with attitudes to shape behavioral intentions, offering practical implications for designing targeted interventions to promote solar energy adoption. Understanding these dynamics is essential for improving messaging strategies, fostering favorable attitudes, and driving sustainable energy behaviors.

5.3.2 Path diagram

The following path diagram visually represents the structural relationships tested within the theoretical model, highlighting the direct effects of heuristics on attitudes and the subsequent influence of attitudes on intentions toward solar energy adoption. Specifically, the availability heuristic, anchoring and adjustment heuristic, and representativeness heuristic are shown as predictors of attitudes, with respective path coefficients illustrating their contributions. The strong, positive effect of attitude on intention further reinforces its central role within the model. The path coefficients (β) indicate the strength of each relationship, offering a clear overview of the hypothesized connections tested in this study. This diagram serves as a critical tool for understanding the interplay of cognitive heuristics and attitudes within the Theory of Planned Behavior (TPB) framework.

Figure 1: Path diagram



Source: Author (2024)

As observed, the path diagram illustrates the role of heuristics as predictors of attitudes and intentions toward solar energy adoption, emphasizing the central influence of attitudes in shaping adoption behaviors. Building on this, the complementary mediation analysis further explores the indirect pathways, offering a deeper understanding of how cognitive heuristics mediate the relationship between attitudes and intentions.

5.4 Mediation analysis

To conduct the mediation analysis, the construct items were transformed into composite scores by calculating their mean values. This transformation simplifies the model by replacing latent constructs with single observed variables, which reduces measurement error variability. Consequently, slight changes in path coefficients occurred due to scale adjustments and the assumption of perfect construct reliability

This analysis provides exploratory insights into the pathways that connect attitudes to intention toward solar energy adoption, revealing the role of cognitive heuristics in decision-making processes, particularly within sustainability research. These findings contribute to existing knowledge by demonstrating how heuristics simplify complex decision-making, reduce cognitive overload, and provide accessible pathways for individuals to form favorable attitudes and intentions toward adopting sustainable technologies like solar energy.

Table 14: Mediation results

Effect	Path	Estimate (β)	Std. Error	z-value	p-value	95% CI
Direct Effect	ATMEAN → ITMEAN	0.529	0.059	8.922	<0.001	[0.406, 0.642]
Indirect Effect	ATMEAN → CHMEAN → ITMEAN	0.056	0.028	2.005	0.045	[0.009, 0.123]
Total Effect	ATMEAN → ITMEAN	0.586	0.048	12198	<0.001	[0.484, 0.669]

The mediation analysis investigated the role of choice heuristics as a mediator between attitudes and intention toward solar energy adoption, as they represent cognitive shortcuts that reduce the effort required for decision-making in complex contexts, such as adopting renewable technologies. This aligns with the broader literature on heuristics, which highlights their role in simplifying decisions under uncertainty and complements the TPB framework by introducing cognitive processes that influence behavioral intentions.

The results showed that attitudes significantly and positively influenced choice heuristics, with a path coefficient of $\beta = 0.480$ ($p < 0.001$). This finding suggests that individuals with favorable attitudes toward solar energy are more likely to rely on cognitive shortcuts, such as choice heuristics, to simplify their decision-making processes. Attitudes appear to shape the use of these heuristics, highlighting their role in reducing cognitive effort when evaluating adoption decisions.

The direct effect of choice heuristics on intention was weak but statistically significant, with a path coefficient of $\beta = 0.118$ and a p-value of 0.044. While the effect size was small, this result indicates that cognitive heuristics contribute positively to adoption intentions. Choice heuristics provide a supplementary mechanism that simplifies complex decisions, particularly in the context of new and uncertain technologies like solar energy.

The mediation analysis revealed partial mediation, where choice heuristics served as an additional pathway linking attitudes to intention. The indirect effect of 0.056 was significant ($p = 0.045$), confirming that while attitudes have a strong direct influence on intentions, choice heuristics partially mediate this relationship. This result aligns with the guidelines of Hair Jr. (2018) and Kline (2015), who emphasize that partial mediation occurs when a mediator explains part, but not all, of the relationship between an independent variable and a dependent variable.

It is important to acknowledge the limitations associated with performing the mediation analysis using a construct that demonstrated poor performance in the measurement model assessment. While choice heuristics exhibited reliability and discriminant validity issues in the measurement phase, their inclusion in the structural model was guided by the principle of statistical parsimony. The decision to exclude the construct from the final structural model ensured the robustness of the primary results while maintaining theoretical rigor. To address this limitation, the supplementary mediation analysis serves as a complementary exploration, providing additional insights into the relationships hypothesized during the development phase.

By balancing statistical parsimony with theoretical contributions, this analysis maintains alignment with the proposed research framework, offering a nuanced understanding of the role of choice heuristics as a mediator within the TPB framework.

6. Discussion of Findings

This study integrates psychological theories that investigate behavioral planning and decision-making, specifically, Ajzen's (1991) Theory of Planned Behavior (TPB) and Prospect Theory, represented by cognitive heuristic variables (Kahneman & Tversky, 1979), to offer a novel perspective on solar energy adoption. By examining heuristics such as availability, representativeness, and anchoring within the sustainable energy decision-making domain, this research provides a novel framework highlighting underexplored psychological factors in this field.

Following Gill and Dolan's (2015) assertion that originality stems from combining established concepts in new ways or applying them to unexplored contexts, this research accomplishes both. The findings confirm that heuristics are substantial predictors of attitude within the TPB framework, applying the model to solar energy adoption studies. As posited by Ajzen (1991), attitude remains a central predictor of intention toward solar energy adoption, evidenced by its significant path coefficient ($\beta = .800$, $p < .05$) and high explanatory power (R^2.632). This result aligns with previous research employing the TPB to investigate solar energy adoption in other contexts.

Heuristic predictors of attitude also played a significant role, collectively accounting for an R^2 of .447. Among these, the availability heuristic emerged as the most influential ($\beta = .614$, $p < .05$), emphasizing its importance in shaping perceptions through vivid and relatable information (Kahneman & Tversky, 1979). This finding highlights the complementary roles of heuristics and attitudes in decision-making. Heuristics serve as foundational cognitive shortcuts, enhancing the predictive power of attitudes and ultimately driving behavioral intentions. The availability heuristic demonstrates the cognitive impact of accessible and relatable information in fostering favorable perceptions of solar energy adoption.

Additionally, the Q^2 for heuristic predictors revealed relative predictive relevance (Q² = .302). According to Hair et al. (2019) and Kline (2016), this score ensures a reasonably sound predictive model. The f^2 effect sizes for availability, anchoring, and representativeness heuristics were .211, .051, and .005, respectively. These metrics highlight the role of heuristics in shaping attitudes, consistent with established practices in structural equation modeling that emphasize $Q^2$and f^2as measures of predictive accuracy and effect size (Hair et al., 2019). This endeavor paves the way for further exploration into how these cognitive strategies can enhance decision-making frameworks in the context of solar energy adoption or other subjects. Future research should focus on cultural, socioeconomic, and technological variables that may interact with heuristics to influence adoption behaviors, providing a comprehensive understanding of their potential impact. The heuristics examined further illuminate the cognitive processes influencing adoption, complementing the evaluation of objective subjects within conventional rational theories (e.g., Rational Choice Theory, Expected Utility Theory, and Multi-Attribute Utility Theory).

These findings align directly with the heuristic investigation program initiated by Kahneman and Tversky (1979), which established heuristics as cognitive strategies used under uncertainty. Furthermore, this research incorporates aspects of Gigerenzer's ecological rationality framework, addressing the complexities and uncertainties inherent in solar energy adoption decisions and the overwhelming information that decision-makers must process. The availability heuristic (H2) demonstrated a significant and moderately strong influence on attitudes ($\beta = .614$, $p < .05$). This finding suggests that vivid and relatable information, such as success stories or visible installations in one's community, plays a pivotal role in shaping favorable perceptions of solar energy. Providing clear and concise information about solar energy systems, installation processes, and financial incentives can help consumers make informed decisions. The findings reinforce that effective, tailored, and segmented messages yield a relevant impact on energy transition action by different actors and their agencies (Endrejat et al., 2020; Guibentif & Patel, 2024).

In contrast, the anchoring and adjustment heuristic (H3) displayed a weaker, marginally significant impact on attitudes ($\beta = .185$, $p = .07$), indicating that initial reference points, like installation costs, hold some influence but are less impactful in shaping perceptions (Fazal et al., 2023). Unexpectedly, the representativeness heuristic (H4) did not significantly influence attitudes ($\beta = -.095$, $p = .204$). This outcome is suggested to result from contextual aspects, such as regional cultural differences, sample idiosyncrasies, including demographic composition, and the unique context in which the research was conducted. A supplementary mediation analysis provided additional insights into the role of choice heuristics, excluded from the structural model due to reliability and validity issues.

While choice heuristics demonstrated partial mediation between attitudes and intention (indirect effect $\beta = .056$, $p = .045$), their overall influence remained weak. This highlights the complexity of integrating cognitive shortcuts into decision-making frameworks and emphasizes the need for robust measurement instruments. The findings reveal that heuristics serve as cognitive shortcuts that simplify decision-making in solar energy adoption. The availability heuristic, in particular, emerged as a practical tool for promoting favorable attitudes by making the benefits of solar energy more relatable and accessible (Bär et al., 2023). This suggests that targeted communication strategies, such as showcasing real-world examples of successful adoption, could significantly enhance public perceptions.

The weaker influence of the anchoring heuristic highlights the need to address cost-related biases more effectively (Wolske et al., 2018). Strategies like framing initial costs in terms of long-term savings or emphasizing financial incentives could mitigate the anchoring effect and foster more favorable attitudes. The lack of significance for the representativeness heuristic underscores potential misalignments between societal stereotypes of solar energy and the values or priorities of prospective adopters. Further investigation is needed to understand how these mental prototypes interact with other psychological and contextual variables (Kahneman & Frederick, 2002).

This limitation highlights challenges in operationalizing abstract cognitive constructs and underscores the importance of proper adaptation and refinement of survey instruments intended to measure such abstract concepts. Developing a more adequate scale using exploratory factor analysis (EFA) as a foundation, followed by confirmatory approaches to ensure reliability and validity, is suggested before re-conducting the study to further validate the findings (Damásio, 2012). The supplementary mediation analysis, while exploratory, offered preliminary insights but should be interpreted with caution given the construct's measurement issues. A further limitation relates to the sample composition, which primarily included younger, urban, and educated individuals. Although this demographic aligns with the study's focus, the findings may not be generalizable to older or less educated populations, who may encounter different barriers to adoption. Finally, the reliance on self-reported data introduces the potential for social desirability bias, specifically the tendency to over-report environmentally friendly behaviors, as discussed in Koller et al. (2023). Future research should incorporate behavioral data or experimental designs to validate and expand upon these findings.

7. Conclusion

This study provided evidence on the influence of heuristics in shaping the attitude and intention of solar energy adoption. This study challenges the traditional view of heuristics as mere cognitive biases, demonstrating their potential to act as adaptive tools in decision-making. Its findings revealed the nuanced relationships between the availability, anchoring and adjustment, representativeness heuristics on attitude and adoption intention toward solar energy adoption. The results were achieved via PLS-SEM and demonstrated that availability heuristics wielded the major influence on attitude, followed by the Anchoring and Adjustment heuristic. This finding suggests that, for the investigated sample, readily available and comprehensive information about solar energy outweighs concerns about upfront costs in shaping attitudes. This indicates that a well-informed individual, with access to readily available and relatable information about the positive aspects of solar energy, is more likely to reframe the initial cost as an upfront investment, leading to a more conscious understanding of long-term financial and environmental benefits. (Bär et al., 2023)

Another relevant finding, yet unexpected, was the negative influence, and the statistical insignificance, of representativeness heuristic to attitude, this suggests that the respondents are more prone about transitioning to solar energy based more on their individual experience than what they've seen in other people's experience with solar energy adoption. This finding gives an opportunity to assess the degree of peer influence in this kind of decision. The weak negative effective effect allows for further investigation, such as: in which stage of the decision process people rely more on stereotypical experiences, peer influence?

What kind of peers' consumers perceive as closer to their own experience, to take as stereotypical reference? To what extent or how intrinsic values and personality traits interplay with the information a person collects to form their decision?

Collectively, these heuristics have accounted for 44,7% of variance of the attitude variable, while this is a significant finding, it also suggests that consumers engage in a more deliberative approach in evaluating the adoption. This study acknowledges the other complexities for the adoption of solar energy, that could be related to technological assessment, financial planning and infrastructure feasibility of the installation. These aspects compose the main body of the literature regarding solar energy adoption, therefore, these research findings should be considered to complement such objective analysis of financial feasibility and infrastructural barriers (Shakeel et al., 2023; Shakeel & Rajala, 2020).

The exploratory mediation analysis also contributed to understanding the heuristic's influence on solar energy adoption intention, while requiring careful interpretation. The analysis demonstrated a partial mediation between attitude and intention. This finding highlights the importance of assessing cognitive effort within the attitude-intention relationship. The choice heuristic acts as a simplifying mechanism, converting a positive attitude into intention. Although heuristics may not always lead to optimal outcomes, they offer a practical approach to decision-making in real-world scenarios. Choice heuristics simplify the decision-making process, helping individuals conserve cognitive resources and make decisions more quickly. This partial mediation suggests that other factors also influence the relationship between attitude and intention.

It is important to recognize the effort made to operationalize heuristics constructs. Firstly, the scarcity of heuristics-based surveys for consumer behavior, that serves this research design, proved to be challenging. Secondly, given the context in which the scales were found, its adaptation also required an extra effort to efficiently operationalize them. And lastly but not least, the ongoing debate whether heuristics is to be interpreted as rationality deviations or adaptive rationality has notable and compelling arguments for both interpretations, therefore theoretical parsimony and constant critical evaluation were required comply with what was proposed (Gigerenzer & Brighton, 2009; Hansjörg Neth et al., 2014).

By demonstrating the context-dependent nature of heuristics and their potential to serve as strategic tools, this study enriches the epistemology on decision making regarding solar energy. It highlights the need for a more nuanced understanding of heuristics, recognizing their potential to both hinder and facilitate sustainable choices. This research paves the way for future investigations into the complex interplay of heuristics, attitudes, and behaviors in sustainability contexts.

The findings of this research underscore the urgent need for collective action to address climate change and transition towards sustainable energy systems. As highlighted by the Intergovernmental Panel on Climate Change (IPCC, 2022), the window of opportunity to limit global warming to 1.5°C is rapidly closing, and the consequences of inaction are dire. The transition to renewable energy sources, such as solar power, is crucial in mitigating the impacts of climate change and ensuring a sustainable future for all (IPCC, 2022).

This need for a transition to sustainable energy is particularly crucial for Brazil, where the reliance on hydroelectric power makes the country vulnerable to the impacts of climate change on rainfall patterns. Recent droughts have led to unstable water reserves in hydroelectric reservoirs, threatening energy security and underscoring the need for diversification of energy sources (Escobar, 2023)

7.1 Theoretical and practical implications

The contribution of this study is multifaceted with both theoretical and practical implications, firstly it contributes to growing body of knowledge by integrating to the Theory of Planned Behavior cognitive heuristic variables, which yielded relevant empirical evidence that consumer decision-making regarding solar energy is also explained through usage of heuristics.

The research provides a novel understanding of the cognitive dynamics that influence solar energy adoption, demonstrating the applicability of the prospect theory to the subject topic (e.g., loss aversion, framing effects). The study locus also contributes to the body of knowledge by being located at an emerging economy of the global south. By its integration to the TPB framework, the study not only revalidated its importance to solar energy adoption studies, but also, expanded its body of explanation (Chen et al., 2020; Olawale Fatoki & Olawale Fatoki, 2022). By framing its dependent constructs to new relations, that by the time of this dissertations were unexplored.

Regarding practical implications the results provided are nuanced but relevant to marketers and policy makers, as the results presented, information plays a crucial role influencing attitudes toward solar energy adoption, therefore, education and conscientization are necessary to promote positive attitude. This relation proved to be stronger than financial framing of the adoption, hence, it is possible to infer that is possible to "Adjust the anchor" with relatable and accessible information.

Regarding the representativeness heuristic, its inconclusive results, shed light on the necessity to better comprehend the influences of peers and proxy examples, this finding contrasts with the results from (Kimberly S. Wolske et al., 2020; Masrahi et al., 2021; Rode & Müller, 2021), that assert the peer influence to the decision. And sheds light on the individualistic drivers of solar energy adoption.

Furthermore, the evolution of the Energy as a Service (EaaS) sector, regulated by the 14.300/2022 Brazilian federative law is fostering innovation in the sector. Given their goal of offering alternative forms of energy commercialization, companies in the EaaS sector are encouraged by these results to adopt heuristic-driven marketing strategies. The data-driven nature of this sector allows for the development of tailored campaigns that cater to specific demographic idiosyncrasies

In conclusion, the results indicate that availability heuristic is the main predictor of attitude within the designed modeling. The influence of heuristic on planned behavior expands the comprehensiveness of the phenomenon subject to investigation. Furthermore, the model results challenge the idea of an all-rational perspective of decision-making regarding diffusion of innovation by highlighting the importance of heuristic on explaining the phenomenon. It is envisioned that the findings of this study, due to the similarities between solar energy adoption and other sustainable energy innovations, could be applicable to other sectors undergoing energy transitions, provided that appropriate adaptations are made. Beyond that, the global south perspective, of an unexplored locus of the literature offers insights beyond the major investigation hubs, there is, China, United States and Europe (Schulte et al., 2022; Zulu et al., 2021).

This dissertation contributes to the United Nations Sustainable Development Goals (SDGs), particularly SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation, and Infrastructure), SDG 12 (Responsible Consumption and Production), and SDG 13(Climate Action) by addressing key aspects of energy transition in the Global South. Focusing on Brazil, a leading emerging economy, the study provides valuable insights into the factors influencing solar energy adoption in a developing nation context. By examining how heuristics shape consumer attitudes and intentions, the research offers a nuanced understanding of decision-making processes related to sustainable energy choices (UN DESA, 2023),

Furthermore, in accordance with SDG 13 (Climate Action), this research lays the foundation for heuristic-driven strategies that can enhance the uptake of solar energy through individual action. By understanding how cognitive shortcuts influence consumer choices, policymakers and marketers can develop targeted interventions that encourage pro-environmental behaviors (Matthies et al., 2023).

This dissertation also considers the perspectives of environmentally engaged consumers, contributing to a framework for understanding sustainable energy adoption in a relatively unexplored geographical context within the phenomenon studied. Ultimately, the findings underscore the importance of individual actions in mitigating climate change and highlight how a deeper understanding of decision-making processes, as discussed by Roelich & Giesekam, (2019) and Zaval & Cornwell, (2016) particularly the role of heuristics, can contribute to more effective climate action by promoting sustainable choices like solar energy adoption.

7.2 Limitations

This study acknowledges limitations related to methodological design, sample composition, and data collection. Firstly, the non-normality observed in response distributions, likely influenced by social desirability bias, necessitated a non-parametric approach. Despite efforts to mitigate this bias, it likely persisted. Secondly, the sample, comprising highly educated individuals with medium-to-high incomes, limits the generalizability of findings to the broader Brazilian population.

Thirdly, the cross-sectional design restricts inferences about changes in variables over time. Additionally, the measurement performance of some scales highlights the need for more robust adaptation techniques. Lastly, the concentration of respondents in the northeastern region, known for high solar incidence, may have influenced attitudes toward solar energy adoption. By addressing these limitations, this section highlights the challenges encountered during the study and provides a basis for future research recommendations.

7.3 Guidance for future research

Building upon the foundation laid by this research, several compelling avenues for future research emerge. One area that warrants further investigation is the unexpected finding regarding the representativeness heuristic. It has been suggested that consumers may be moving beyond stereotypes when evaluating solar energy, prompting further exploration of the role of social norms and peer influence in solar energy adoption. It is plausible that consumers are less influenced by general stereotypes but more influenced by the behaviors and opinions of those within their social circles. This suggests that strategies focusing on community engagement and social proof could be particularly effective. Future research could investigate how to leverage these social influences to promote solar energy adoption.

Another promising avenue is to explore the dynamic nature of heuristics and their interplay with other cognitive processes. Qualitative methods like in-depth interviews could provide rich insights into how consumers utilize heuristics in different contexts. Furthermore, incorporating physiological measures, such as eye-tracking, could offer objective data on real-time cognitive processing during decision-making.

From a marketing perspective, future research could investigate the effectiveness of different communication channels and message framing in conveying the benefits of solar energy. Comparing the impact of visual versus textual information, or narrative-based versus factual presentations, could reveal valuable insights for optimizing marketing campaigns.

Additionally, addressing the limitations encountered with measuring choice heuristics is crucial. This suggests that the scale may not have adequately captured the complexity of the choice heuristic construct or may have suffered from translation or adaptation issues.

Additionally, the study's sample, whi was predominantly young, urban, and educated, may have influenced the results, as different demographics may exhibit varying reliance on choice heuristics. Other unidentified variables, such as cultural factors or prior experiences with solar energy, may have also influenced the choice heuristic and its relationship with other constructs in the study. Addressing these issues in future research could enhance the understanding of the role of choice heuristics in sustainable consumer behavior.

Exploring alternative methodologies, such as experimental designs, could provide a more nuanced understanding of the causal relationships between heuristics, attitudes, and intentions. Expanding the research scope to include diverse consumer segments and investigating the interaction of heuristics with emotions, values, and social norms could provide a more complete understanding of sustainable choices.

By pursuing these diverse research avenues, the field can significantly advance its understanding of heuristics, sustainable choices, and consumer behavior. This knowledge can empower the design of more effective interventions that promote solar energy adoption and contribute to a more sustainable future.

7.4 Concluding remarks

The implications of the research findings for energy policy and marketing have been examined in this dissertation. The study has highlighted the importance of considering heuristics and consumer psychology in designing effective interventions to promote solar energy adoption. The findings suggest that policymakers and marketers can leverage the power of heuristics to shape consumer perceptions, reframe costs and benefits, and encourage sustainable choices.

This research serves as a call to action for policymakers, marketers, and individuals to recognize the potential of heuristics in shaping sustainable choices. It is hoped that the study's findings and implications will inspire and inform efforts to promote solar energy adoption and contribute to a more sustainable world.

By understanding the interplay of heuristics, attitudes, and intentions, consumers can be empowered to make informed choices that align with their values and contribute to a more sustainable world. It is acknowledged that this study has limitations, including those related to sample composition, data collection methods, and the scope of the research. These limitations highlight opportunities for future research to delve deeper into the complex dynamics of sustainable energy adoption.

As the urgent need to address climate change is grappled with by the world, this research serves as a call to action for policymakers, marketers, and individuals alike. The way toward a future where sustainable choices are not just an aspiration, but a reality can be collectively paved by embracing the transformative potential of solar energy and harnessing the power of heuristic

References

Abreu, A., Wingartz, C., & Hardy, S. (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

Agarwal, R., Bhadauria, A., Swami, S., & Rajwnashi, R. (2023). Factors influence or inhibit the purchase intention towards rooftop solar: Using structural equation modeling and importance performance map analysis approach. *Journal of Cleaner Production, 410*, 137109. https://doi.org/10.1016/j.jclepro.2023.137109

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2015). The theory of planned behaviour is alive and well, and not ready to retire: A commentary on Sniehotta, Presseau, and Araújo-Soares. *Health Psychology Review, 9*(2), 131–137. https://doi.org/10.1080/17437199.2014.883474

Ajzen, I., & Fishbein, M. (2012). Values, Attitudes, and Behavior. In *Understanding Attitudes and Predicting Social Behavior* (pp. 33–38). https://doi.org/10.1007/978-3-531-18898-0_5

Akrofi, M. M., & Okitasari, M. (2023). Beyond costs: How urban form could limit the uptake of residential solar PV systems in low-income neighborhoods in Ghana. *Energy for Sustainable Development, 74*, 20–33. https://doi.org/10.1016/j.esd.2023.03.004

Alessandro Von Gal, A., Fabiani, G., & Piccardi, L. (2024). Climate change anxiety, fear, and intention to act. *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2024.1341921

Alipour, M., Salim, H., Stewart, R. A., & Sahin, O. (2021). Residential solar photovoltaic adoption behaviour: End-to-end review of theories, methods and approaches. *Renewable Energy*, *170*, 471–486. https://doi.org/10.1016/j.renene.2021.01.128

Alogdianakis, F., & Dimitriou, L. (2023). Optimal mechanism design of public policies for promoting electromobility: A dynamic programming formulation. *Transportation Research Interdisciplinary Perspectives*, *19*, 100807. https://doi.org/10.1016/j.trip.2023.100807

Armenia, S., Arquitt, S., Pedercini, M., & Pompei, A. (2022). Anticipating human resilience and vulnerability on the path to 2030: What can we learn from COVID-19? *Futures*, *139*, 102936. https://doi.org/10.1016/j.futures.2022.102936

Bailey, C., Garcia, S., Liang, H., Ross, K., Quinn, J., & Quinn, J. D. (2021). Energy Supply Readiness Across Climate Change and Energy Demand Scenarios in the Columbia River Basin. *Systems and Information Engineering Design Symposium*. https://doi.org/10.1109/sieds52267.2021.9483778

Bär, D., Feuerriegel, S., Li, T., & Weinmann, M. (2023). Message framing to promote solar panels. *Nature Communications*, *14*(1), Artigo 1. https://doi.org/10.1038/s41467-023-42904-0

Best, R., Chareunsy, A., & Taylor, M. (2023). Emerging inequality in solar panel access among Australian renters. *Technological Forecasting and Social Change*, *194*, 122749. https://doi.org/10.1016/j.techfore.2023.122749

Bhardwaj, A., Joshi, M., Khosla, R., & Dubash, N. K. (2019). More priorities, more problems? Decision-making with multiple energy, development and climate objectives. *Energy Research & Social Science*, *49*, 143–157. https://doi.org/10.1016/j.erss.2018.11.003

Brunet, C., Savadogo, O., Baptiste, P., Bouchard, M. A., Cholez, C., Rosei, F., … Merveille, N. (2022). Does solar energy reduce poverty or increase energy security? A comparative analysis of sustainability impacts of on-grid power plants in Burkina Faso, Madagascar, Morocco, Rwanda, Senegal and South Africa. *Energy Research & Social Science*, *87*, 102212. https://doi.org/10.1016/j.erss.2021.102212

Byrne, B. (2010). *Structural equation modeling with AMOS - basic concepts, applications, and programming* (2nd ed.). Multivariate applications series.

Carpino, C., Bruno, R., Carpino, V., & Arcuri, N. (2022). Improve decision-making process and reduce risks in the energy retrofit of existing buildings through uncertainty and sensitivity analysis. *Energy for Sustainable Development*, *68*, 289–307.

Chen, M.-F. (2020). The impacts of perceived moral obligation and sustainability self-identity on sustainability development: A theory of planned behavior purchase intention model of sustainability-labeled coffee and the moderating effect of climate change skepticism. *Business Strategy and The Environment*, *29*(6), 2404–2417. https://doi.org/10.1002/bse.2510

Cooksey, R. W. (2020). Descriptive Statistics for Summarising Data. Em R. W. Cooksey (Org.), *Illustrating Statistical Procedures: Finding Meaning in Quantitative Data* (p. 61–139). Springer. https://doi.org/10.1007/978-981-15-2537-7_5

Creswell, J. D., & Creswell, J. W. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). 21. Daniel Kahneman, D., Tversky, A. (1982). The Psychology of Preferences. *Scientific American*, *246*(1), 160–173. https://doi.org/10.1038/scientificamerican0182-160

David Goretzko, D., Pham, T. T. H., Bühner, M. (2019). Exploratory factor analysis: Current use, methodological developments and recommendations for good practice. *Current Psychology*, *40*(7), 3510–3521. https://doi.org/10.1007/s12144-019-00300-2

Duan, M., Li, L., Liu, X., Pei, J., & Song, H. (2023). Turning awareness into behavior: Meta-analysis of household residential life energy transition behavior from the dual perspective of internal driving forces and external inducing forces. *Energy*, *279*, 128072. https://doi.org/10.1016/j.energy.2023.128072

Durmaz, A., Dursun, İ., & Kabadayı, E. T. (2022). Are They Actually Sustainable? The Social Desirability Bias in Sustainable Consumption Surveys. Em J. Bhattacharyya (Org.), *Dealing with Socially Responsible Consumers: Studies in Marketing* (p. 533–560). Springer Nature. https://doi.org/10.1007/978-981-19-4457-4_28

Evans, J. S. B. T. (2019). Reflections on reflection: The nature and function of type 2 processes in dual-process theories of reasoning. *Thinking & Reasoning*, *25*(4), 383–415. https://doi.org/10.1080/13546783.2019.1623071

Fathima, H., Moideen Batcha, R., Sankar Ganesh, R., & Ansari Sarwar Alam, A. (2022). Factors affecting consumer purchase intention for buying solar energy products. *International Journal of Energy Sector Management*. https://doi.org/10.1108/ijesm-04-2022-0002

Fazal, S., Hayat, N., & Mamun, A. (2023). Renewable Energy and Sustainable Development—Investigating Intention and Consumption among Low-Income Households in an Emerging Economy. *Sustainability*, *15*(21), 15387*. https://doi.org/10.3390/su152115387

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312

Gangakhedkar, R., & Karthik M, K. (2023). Behavioural Theories and Purchase Intention of Renewable Energy Technologies—A Meta-Analysis. *Journal of Infrastructure Development*, *14*, 141–159. https://doi.org/10.1177/09749306221140737

George Adwek, G., Shen, B., Arowo, M., Ndolo, P., … Shimmon, J. (2019). Review of solar energy development in Kenya: Opportunities and challenges. *Renewable Energy Focus*, *29*, 123–140. https://doi.org/10.1016/j.ref.2019.03.007

Ghosh, A., & Satya Prasad, V. K. (2024). Evaluating the influence of environmental factors on household solar PV pro-environmental behavioral intentions: A meta-analysis review. *Renewable and Sustainable Energy Reviews*, *190*, 114047. https://doi.org/10.1016/j.rser.2023.114047

Gigerenzer, G. (2008). Why Heuristics Work. *Perspectives on Psychological Science*, *3*(1), 20–29. https://doi.org/10.1111/j.1745-6916.2008.00058.x

Gigerenzer, G. (2024). Can psychology learn from the natural sciences? *Theory & Psychology*, *34*(3), 295–310.

Hsien-Long Huang, H., Li-Keng Cheng, L. (2022). Predicting intention of residential solar installation: The role of ecological lifestyle, consumer innovativeness, perceived benefit, government incentives, and solar product knowledge. *Energy & Environment*, *33*(7), 1426-1443. https://doi.org/10.1177/0958305x221100525

Huansuriya, T., & Ariyabuddhiphongs, K. (2023). Predicting Residential Photovoltaic Adoption Intention of Potential Prosumers in Thailand: A Theory of Planned Behavior Model. *Energies*, *16*(17), 6337. https://doi.org/10.3390/en16176337

Hunt, S. D. (1991). Positivism and Paradigm Dominance in Consumer Research: Toward Critical Pluralism and Rapprochement. *Journal of Consumer Research*, *18*(1), 32–44. https://doi.org/10.1086/209238

Idrees Waris, I., Hameed, I., Ali, R. (2022). Predicting household sign up for solar energy: An empirical study based on the extended theory of planned behavior. *International Journal of Energy Sector Management*. https://doi.org/10.1108/ijesm-06-2021-0010

International Test Commission. (2017). *The ITC Guidelines for Translating and Adapting Tests* (Second edition). https://www.intestcom.org/files/guideline_test_adaptation_2ed.pdf

Jason W. Osborne, J., Costello, A. B. (2009). Best Practices in Exploratory Factor Analysis: Four Recommendations for Getting the Most from Your Analysis. *Pan-Pacific Management Review*, *10*(7), 131–146. https://doi.org/10.7275/jyj1-4868

Jiang, F., Ma, J., Webster, C. J., Chiaradia, A. J. F., Zhou, Y., Zhao, Z., & Zhang, X. (2023). Generative urban design: A systematic review on problem formulation, design generation, and decision-making. *Progress in Planning*, 100795. https://doi.org/10.1016/j.progress.2023.100795

Jindal, A., & Shrimali, G. (2022). At scale adoption of battery storage technology in Indian power industry: Enablers, frameworks and policies. *Technological Forecasting and Social Change*, *176*, 121467. https://doi.org/10.1016/j.techfore.2021.121467

K. Ukoba, K., Yoro, K., Eterigho-Ikelegbe, O., Ibegbulam, C., & Jen, T. (2024). Adaptation of solar energy in the Global South: Prospects, challenges and opportunities. *Heliyon*. https://doi.org/10.1016/j.heliyon.2024.e28009

Kahneman, D., & Tversky, A. (1979). PROSPECT THEORY: AN ANALYSIS OF DECISION UNDER RISK. *Econometrica*, *47*(2), 263–291. https://doi.org/10.1017/cbo9780511609220.014

Kause, A., Townsend, T., Gaissmaier, W. (2019). Framing Climate Uncertainty: Frame Choices Reveal and Influence Climate Change Beliefs. *Weather, Climate, and Society*, *11*(1), 199–215. https://doi.org/10.1175/wcas-d-18-0002.1

Kimberly S. Wolske, K., Gillingham, K., 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

Kline, R. B. (2011). *Principles and practice of structural equation modeling* (3rd ed.).

Kline, R. B. (2016). *Principles and practice of structural equation modeling, 4th ed* (p. xvii, 534). Guilford Press.

Korcaj, L., Hahnel, U. J. 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

Korteling, J. E., Paradies, G. L., & Sassen-van Meer, P. (2023). Cognitive bias and how to improve sustainable decision making. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1129835

Kruglanski, A. W., Ajzen, I. (1983). Bias and error in human judgment. *European Journal of Social Psychology*, *13*(1), 1–44. https://doi.org/10.1002/ejsp.2420130102

Kumar, N., Kumar, T., Nema, S., & Thakur, T. (2023). Reliability oriented techno- economic assessment of fast charging stations with photovoltaic and battery systems in paired distribution & urban network. *Journal of Energy Storage*, *72*, 108814. https://doi.org/10.1016/j.est.2023.108814

Kyere, F., Dongying, S., Bampoe, G. D., Kumah, N. Y. G., & Asante, D. (2024). Decoding the shift: Assessing household energy transition and unravelling the reasons for resistance or adoption of solar photovoltaic. *Technological Forecasting and Social Change*, *198*, 123030. https://doi.org/10.1016/j.techfore.2023.123030

Leduchowicz-Municio, A., Domenech, B., Ferrer-Martí, L., Morales Udaeta, M. E., & Veiga Gimenes, A. L. (2023). Women, equality, and energy access: Emerging lessons for last-mile rural electrification in Brazil. *Energy Research & Social Science*, *102*, 103181–103181. https://doi.org/10.1016/j.erss.2023.103181

Li, C.-H. (2016). Confirmatory factor analysis with ordinal data: Comparing robust maximum likelihood and diagonally weighted least squares. *Behavior Research Methods*, *48*(3), 936–949. https://doi.org/10.3758/s13428-015-0619-7

Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology, 22*(140), 55–55.

Liu, L. (2024). Exploring the emerging trends of energy discourse: A Bibliometric Analysis. *Energy Strategy Reviews*, *52*, 101338. https://doi.org/10.1016/j.esr.2024.101338

Loveldy, Z. (2021). Examining the Attitude-Behavior Gap and Adoption Intention of SHS Technology. *International Journal of Applied Business Research, 3*(1), 14–24. https://doi.org/10.35313/ijabr.v3i1.119

Maibach, E. (2019). Biodiversity and Climate Change. In T. E. Lovejoy & L. Hannah (Eds.), *Transforming the Biosphere* (pp. 344–354). Yale University Press. https://doi.org/10.12987/9780300241198-040

Malhotra, N. K. (2010). Marketing Research: An Applied Orientation: Global Edition (6th ed.).

Marquardt, J., Fünfgeld, A., & Elsässer, J. P. (2023). Institutionalizing climate change mitigation in the Global South: Current trends and future research. Earth System Governance, 15, 100163. https://doi.org/10.1016/j.esg.2022.100163

Martin Klein, M., Deissenroth, M. (2017). When do households invest in solar photovoltaics? An application of prospect theory. Energy Policy, 109, 270–278. https://doi.org/10.1016/j.enpol.2017.06.067

Masrahi, Wang, & Abudiyah. (2021). Factors influencing consumers’ behavioral intentions to use renewable energy in the United States residential sector. Energy Reports, 7, 7333–7344. https://doi.org/10.1016/j.egyr.2021.10.077

Matsueda, R. L. (2012). Key advances in the history of structural equation modeling.

Matthies, E., de Paula Sieverding, T., Engel, L., & Blöbaum, A. (2023). Simple and Smart: Investigating Two Heuristics That Guide the Intention to Engage in Different Climate-Change-Mitigation Behaviors. Sustainability, 15(9), Artigo 9. https://doi.org/10.3390/su15097156

Meinert, D. B., & Krämer, N. C. (2022). How the expertise heuristic accelerates decision-making and credibility judgments in social media by means of effort reduction. PloS One, 17(3), e0264428. https://doi.org/10.1371/journal.pone.0264428

Mohamad Hjeij, M., & Vilks, A. (2023). A brief history of heuristics: How did research on heuristics evolve? Humanities and Social Sciences Communications, 10(1). https://doi.org/10.1057/s41599-023-01542-z

Morgan Taylor, M., Marsh, E. J., & Samanez-Larkin, G. R. (2023). Heuristic decision-making across adulthood. Psychology and Aging. https://doi.org/10.1037/pag0000726

Moscati, I. (2023). The History and Methodology of Expected Utility. Elements in Decision Theory and Philosophy. https://doi.org/10.1017/9781009198295

Mousavi, S., & Gigerenzer, G. (2017). Heuristics are Tools for Uncertainty. Homo Oeconomicus, 34(4), 361–379. https://doi.org/10.1007/s41412-017-0058-z

Mutumbi, A., Thondhlana, G., & Ruwanza, S. (2024). Adoption of residential rooftop solar PV systems in South Africa: A scoping review of barriers. Heliyon, 10(10), e30937. https://doi.org/10.1016/j.heliyon.2024.e30937

Muwanga, R., Ssekakubo, J., Nalweyiso, G., Aarakit, S., & Kusasira, S. (2024). Do all forms of public attitudes matter for behavioural intentions to adopt solar energy technologies (SET) amongst households? Technological Sustainability, 3(1), 96–112. https://doi.org/10.1108/TECHS-08-2023-0031

Nathan Novemsky, N., Kahneman, D. (2005). The boundaries of loss aversion. Journal of Marketing Research, 42(2), 119–128. https://doi.org/10.1509/jmkr.42.2.119.62292

Neys, W. D. (2023). Advancing theorizing about fast-and-slow thinking. Behavioral and Brain Sciences, 46, e111. https://doi.org/10.1017/S0140525X2200142X

Olawale Fatoki. (2022). Determinants of Intention to Purchase Photovoltaic Panel System: An Integration of Technology Acceptance Model and Theory of Planned Behaviour. International Journal of Energy Economics and Policy, 12(3), 432–440. https://doi.org/10.32479/ijeep.12931

Oliver Alexander Gansser, O., & Reich, C. S. (2022). Influence of the New Ecological Paradigm (NEP) and environmental concerns on pro-environmental behavioral intention based on the Theory of Planned Behavior (TPB). Journal of Cleaner Production, 382, 134629–134629. https://doi.org/10.1016/j.jclepro.2022.134629

Orçan, F. (2018). Exploratory and Confirmatory Factor Analysis: Which One to Use First? Eğitimde ve Psikolojide Ölçme ve Değerlendirme Dergisi, 9(4), 414–421. https://doi.org/10.21031/epod.394323

Palm, A., & Lantz, B. (2020). Information dissemination and residential solar PV adoption rates: The effect of an information campaign in Sweden. Energy Policy, 142, 111540. htts://doi.org/10.1016/j.enpol.2020.111540

Parker, D. P. (2023, April 4). Let the Sun In: The Effect of Investment Tax Credits on Solar Energy Generation Across the United States. https://www.proquest.com/openview/225dd684533ebfec6aea1bf1e1a60e2c/1?pq-origsite=gscholar&cbl=18750&diss=y

Queiroz, J. V., Borges, K. K., Queiroz, F. C. B. P., Lima, N. C., da Silva, C. L., & de Souza Morais, L. (2020). Barriers to expand solar photovoltaic energy in Brazil. Independent Journal of Management & Production, 11(7), 2733–2754. https://doi.org/10.14807/ijmp.v11i7.1098

Rai, V., & Robinson, S. A. (2013). Effective Information Channels for Reducing Costs of Environmentally-Friendly Technologies: Evidence from Residential PV Markets. Environmental Research Letters. https://doi.org/10.1088/1748-9326/8/1/014044

Rick H. Hoyle, R. H., Jennifer C. Isherwood, J. C. (2013). Reporting Results from Structural Equation Modeling Analyses in Archives of Scientific Psychology. Archives of Scientific Psychology, 1(1), 14–22. https://doi.org/10.1037/arc0000004

Rode, J., & Müller, S. (2021). I Spot, I Adopt! Peer Effects and Visibility in Solar Photovoltaic System Adoption of Households (SSRN Scholarly Paper 3469548). https://doi.org/10.2139/ssrn.3469548

Romanova, E. S., & Masalkova, A. A. (2021). Risks of switching to renewable energy sources. E3S Web of Conferences, 101, 01010. https://doi.org/10.1051/shsconf/202110101010

Sadler-Smith, E. (2023). 56 How Gut Feeling Sometimes Gets It Right: Fast and Frugal Heuristics. In E. Sadler-Smith (Ed.), *Intuition in Business* (p. 0). Oxford University Press. https://doi.org/10.1093/oso/9780198871569.003.0003

Santika, W. G., Urmee, T., Simsek, Y., Bahri, P. A., & Anisuzzaman, M. (2020). An assessment of energy policy impacts on achieving Sustainable Development Goal 7 in Indonesia. *Energy for Sustainable Development, 59*, 33–48. https://doi.org/10.1016/j.esd.2020.08.011

Savalei, V. (2021). Improving Fit Indices in Structural Equation Modeling with Categorical Data. *Multivariate Behavioral Research, 56*(3), 390–407. https://doi.org/10.1080/00273171.2020.1717922

Schoemaker, P. J. H. (1982). The Expected Utility Model: Its Variants, Purposes, Evidence and Limitations. *Journal of Economic Literature, 20*(2), 529–563.

Schulte, E., Scheller, F., Pasut, W., & Bruckner, T. (2022). Product traits, decision-makers, and household low-carbon technology adoptions: Moving beyond single empirical studies. *Energy Research & Social Science, 84*, 102367. https://doi.org/10.1016/j.erss.2021.102367

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

Shakeel, S. R., & Rajala, A. (2020). Factors Influencing Households' Intention to Adopt Solar PV: A Systematic Review (p. 282–289). https://doi.org/10.1007/978-3-030-50791-6_36

Shakeel, S. R., Yousaf, H., Irfan, M., & Rajala, A. (2023). Solar PV adoption at household level: Insights based on a systematic literature review. *WOS:001083579400001*. https://osuva.uwasa.fi/handle/10024/16779

Tversky, A., & Kahneman, D. (1974). Judgment Under Uncertainty: Heuristics and Biases. *Science*. https://doi.org/10.1126/science.185.4157.1124

Valentini, F., & Damásio, B. F. (2016). Variância Média Extraída e Confiabilidade Composta: Indicadores de Precisão. *Psicologia: Teoria e Pesquisa*, *32*, e322225. https://doi.org/10.1590/0102-3772e322225

Zulu, S. L., Zulu, E., & Chabala, M. (2021). Factors influencing households' intention to adopt solar energy solutions in Zambia: Insights from the theory of planned behaviour. https://doi.org/10.1108/sasbe-01-2021-0008

8. APPENDIX A : SURVEY ITEMS

SECTION I – Introduction

Dear Participant,

You have been invited to take part in a research study led by researcher Vinicius Azevedo Barbosa. Your participation is a requirement for Vinicius to obtain his Master's degree from the Graduate Program in Management, Innovation, and Consumption (PPGIC-UFPE CAA). This study aims to examine the influence of heuristics on decision-making processes related to the adoption of solar energy. Your involvement is greatly appreciated.

Heuristics are mental strategies designed to simplify decision-making, allowing us to deal with complex information more quickly and efficiently. They facilitate instant choices and are applied in decisions requiring detailed technical analysis, such as the adoption of solar energy in homes. In this scenario, heuristics shape our perception of the costs, benefits, and risks associated with solar energy, playing a crucial role in determining the consumer's final decision.

All questions below will be measured using a scale from 1 to 7, where 1 means strongly disagree and 7 means strongly agree with the statements presented. There are no right or wrong answers.

This questionnaire requires less than 6 minutes of your attention.

Before responding, please read the "Informed Consent Form," if you agree to participate in this research, check the YES option and proceed to the next section.

Participation in this study is voluntary, and your responses will be treated confidentially. There are no right or wrong answers; we are only interested in your opinion and experience.

SECTION II – INFORMED CONSENT FORM

The document, called the Informed Consent Form (ICF), aims to ensure your rights and duties as a participant in this research.

Please read it carefully. If you have any questions about the research, do not wish to participate, or wish to withdraw your authorization at any time during the study, there will be no penalty or harm to you.

The knowledge resulting from this study will consist of statistical data. Participants will not be mentioned or identified at any time during the analysis and dissemination of results. Your participation is confidential, voluntary, and very important, as it will generate helpful information only for this research. The treatment of collected data will follow the determinations of the General Data Protection Law (LGPD - Law 13.709/18).

If you have any questions about the research, you can contact us at the following email: vinicius.abarbosa@ufpe.br.

As there will be no respondent identification, to receive a summary of the results obtained from this research, please contact us at the email mentioned above.

I agree to participate in this research.

- YES
- NO

SECTION III - Intention

In this section, we would like to know your intention regarding adopting photovoltaic solar energy in your residence. Please indicate your degree of agreement with the following statements, considering 1 for (Strongly Disagree) and 7 for (Strongly Agree).

1.You would use solar energy even if the supply was inconsistent

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

2. The probability that you will start using solar energy is very high

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

3. You plan to use more renewable energy rather than non-renewable energy

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

4. You will consider the use of renewable energy for ecological reasons

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

5. Comparing with non-renewable energy, you are more willing to use renewable energy.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

6. You intend to use solar energy

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

7. If you have an opportunity, you will consider using solar energy because they are less polluting

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

8. You would opt to change to solar energy if you had the choice

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

SECTION IV – Attitude

In this section, we would like to know your attitude towards solar and renewable energy. Please indicate your degree of agreement with the following statements, considering 1 for (Strongly Disagree) and 7 for (Strongly Agree).

1. Using solar energy is beneficial for the environment.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

2. Solar energy can help reduce energy costs in the long run.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

3.I believe that renewable energy is a reliable source of energy.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

4.Using renewable energy is a good idea.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

5.I am interested in learning more about renewable energy.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

6. I support the use of renewable energy in my community.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

SECTION V - Choice Heuristics

In this section, we would like to know how you make decisions regarding the adoption of solar energy. Please indicate your degree of agreement with the following statements, considering 1 for (Strongly Disagree) and 7 for (Strongly Agree).

1.The potential installation costs would influence your decision-making process.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

2.I believe that installing solar panels would increase the value of my home.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

3. Potential savings are important to you when considering the adoption of solar energy.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

4. The potential installation costs would influence your decision-making process.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

5. You trust reviews and recommendations from other people when considering the adoption of solar energy.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

SECTION VI - Representativeness Heuristics

In this section, we would like to know how you perceive and evaluate information related to solar energy. Please indicate your degree of agreement with the following statements, considering 1 for (Strongly Disagree) and 7 for (Strongly Agree).

1.Lower installation costs would encourage me to seriously consider installing solar panels.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

2.I estimate how much I will pay for energy based on how much I have paid lately.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

3. I believe that my current energy provider is able to maintain the quality of service provided.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

4. I actively avoid electricity suppliers with a bad reputation.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

Section VII - Anchoring and Adjustment Heuristics

In this section, we would like to know how you adjust your decisions based on previous information and experiences related to solar energy. Please indicate your degree of agreement with the following statements, considering 1 for (Strongly Disagree) and 7 for (Strongly Agree).

1. I would postpone my decision to adopt solar energy if I heard negative news about it.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

2. When considering the installation of solar panels, I tend to base my decision on the initial cost of installation.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

3. Potential savings are important to you when considering the adoption of solar energy.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

4. To decide to adopt solar energy, I would compare my electricity bill with the potential benefits of solar energy systems.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

5. If I notice a consistent increase in my electricity bill, I am more likely to consider adopting solar energy.

Strongly Disagree 1 2 3 4 5 6 7 Strongly Agree

SECTION VIII – Respondent Profile

01. Gender

o Male

o Female

o Other: _______________

02. What is your age? (e.g., 25)

o _____________

03. Marital status

o Single

o Married/Cohabiting

o Divorced/Separated

Widowed

04. In which region you reside?

- North
- Northeastern
- Midwest
- South
- Southeast

05. Education (indicate the highest level of education you have completed)

o Elementary School

o High School

o Higher Education

o Lato Sensu Postgraduate (e.g., Specialization and/or MBA - master’s in business administration)

o Stricto Sensu Postgraduate (e.g., Master's and/or Academic and/or Professional Doctorate)

07. Monthly income (enter numbers only, e.g., 1500)

o ______________

08. Including yourself, how many people live in your house?

o ______________

SECTION IX – Acknowledgements

We would like to thank you for your cooperation in this research! You can continue to help us by sharing the link to this questionnaire with people you believe could contribute to this research.

Would you like to receive the results of this research when it is published? If so, please leave your email below (Optional).

If you wish, leave suggestions/comments in this field (Optional).

9. APPENDIX B: Jasp PLS SEM Outuput

Table 15: Model fit indices

Model fit	Baseline test					
	AIC	BIC	n	χ^2	df	p
Formative model	15.487.306	15.577.930	380	577.585	97	1.916×10^{-69}

Source: Author(2024)

Table 16: PLS-SEM Variance Explained

R-Squared		
Outcome	R^2	Adjusted R^2
ATTITUDE	0.447	0.442
INTENTION	0.632	0.631

Source: Author(2024)

Table 17: Reliability measures

Reliability Measures			
Latent	Cronbach's α	Jöreskog's ρ	Dijkstra-Henseler's ρ
AVAILABILITY	0.692	0.703	0.720
ANCHORING_AND_ADJUSTMENT	0.721	0.719	0.732
REPRESENTATIVENESS	0.697	0.701	0.876
ATTITUDE	0.808	0.806	0.826
INTENTION	0.688	0.695	0.708

Source: Author(2024)

Table 18: Parameter estimates

Factor Weights						95% Confidence Interval	
Construct	Indicator	Estimate	Std. Error	z-value	p-value	Lower	Upper
AVAILABILITY	AV1	0.332	0.057	5.805	3.212×10^{-9}	0.214	0.438
	AV3	0.488	0.041	11.829	1.388×10^{-32}	0.410	0.569
	AV4	0.429	0.032	13.505	7.316×10^{-42}	0.370	0.493
ANCHORING_AND_ADJUSTMENT	AA2	0.472	0.049	9.546	6.726×10^{-22}	0.384	0.579
	AA3	0.350	0.040	8.760	9.791×10^{-19}	0.262	0.423

	AA4	0.419	0.050	8.384	2.551×10^{-17}	0.335	0.534
REPRESENTATIVENESS	RP1	0.452	0.038	12.038	1.116×10^{-33}	0.380	0.527
	RP2	0.607	0.047	12.903	2.162×10^{-38}	0.528	0.715
	RP3	0.127	0.074	1.716	0.043	-0.030	0.257
ATTITUDE	AT1	0.385	0.032	11.945	3.461×10^{-33}	0.332	0.459
	AT4	0.258	0.026	9.976	9.747×10^{-24}	0.203	0.305
	AT5	0.307	0.023	13.217	3.485×10^{-40}	0.265	0.357
	AT6	0.294	0.019	15.212	1.467×10^{-52}	0.256	0.334
INTENTION	IT2	0.360	0.028	12.741	1.746×10^{-37}	0.307	0.419
	IT3	0.485	0.028	17.037	2.187×10^{-65}	0.432	0.543
	IT4	0.417	0.028	14.692	3.654×10^{-49}	0.362	0.475

Source: Author(2024)

Table 19: Factor Loadings

Factor Loadings								
Construct	Indicator	Estimate	Std. Error	z-value	p-value	95% Confidence Interval	
						Lower	**Upper**
AVAILABILITY	AV1	0.529	0.094	5.655	7.796×10-9	0.337	0.699
	AV3	0.778	0.070	11.175	2.692×10-29	0.628	0.903
	AV4	0.685	0.060	11.445	1.249×10-30	0.561	0.797
ANCHORING_AND_ADJUSTMENT	AA2	0.773	0.078	9.886	2.382×10-23	0.608	0.919
	AA3	0.577	0.089	6.484	4.470×10-11	0.388	0.732
	AA4	0.685	0.076	9.034	8.289×10-20	0.536	0.837
REPRESENTATIVENESS	RP1	0.687	0.070	9.817	4.736×10-23	0.533	0.806
	RP2	0.920	0.058	15.929	1.980×10-57	0.783	0.996
	RP3	0.201	0.120	1.669	0.048	-0.037	0.427
ATTITUDE	AT1	0.882	0.040	21.793	1.344×10-105	0.795	0.956
	AT4	0.596	0.084	7.073	7.575×10-13	0.420	0.747
	AT5	0.704	0.054	12.989	7.089×10-39	0.588	0.801
	AT6	0.678	0.068	9.919	1.729×10-23	0.527	0.796
INTENTION	IT2	0.564	0.050	11.269	9.331×10-30	0.464	0.662
	IT3	0.758	0.054	14.073	2.800×10-45	0.643	0.856
	IT4	0.652	0.054	12.139	3.287×10-34	0.542	0.753

Source: Author(2024)

Table 20: Regression coefficient's

Regression Coefficients						95% Confidence Interval			
Outcome	Predictor	Estimate	Std. Error	z-value	p-value	Lower	Upper	f^2	VIF
ATTITUDE	AVAILABILITY	**0.614**	0.148	4.134	1.786×10^{-5}	0.339	0.932	0.272	2.412
	ANCHORING_AND_ADJUSTMENT	**0.185**	0.129	1.435	0.076	-0.074	0.420	0.025	1.963
	REPRESENTATIVENESS	**-0.095**	0.115	-0.828	0.204	-0.338	0.103	0.007	1.917
INTENTION	ATTITUDE	**0.800**	0.046	17.207	1.169×10^{-66}	0.703	0.886	1.721	

Source: Author (2024)

Table 21: Total Effcts

Total effects						95% Confidence Interval	
Outcome	Predictor	Estimate	Std. Error	z-value	p-value	Lower	Upper
ATTITUDE	AVAILABILITY	0.614	0.148	4.134	1.786×10^{-5}	0.339	0.932
	ANCHORING_AND_ADJUSTMENT	0.185	0.129	1.435	0.076	-0.074	0.420
	REPRESENTATIVENESS	-0.095	0.115	-0.828	0.204	-0.338	0.103
INTENTION	AVAILABILITY	0.493	0.129	3.819	6.713×10^{-5}	0.256	0.768
	ANCHORING_AND_ADJ	0.148	0.104	1.430	0.076	-0.059	0.337
	REPRESENTATIVENESS	-0.077	0.093	-0.826	0.204	-0.277	0.081
	ATTITUDE	0.800	0.046	17.207	1.169×10^{-66}	0.703	0.886

Source: Author (2024)

Table 22: Endogenous Prediction Metrics

Endogenous Prediction Metrics					
Indicator	Target MAE	Linear model MAE	Target RMSE	Linear model RMSE	Target Q2 prediction
AT1	0.598	0.725	0.891	0.980	0.173
AT4	0.518	0.718	0.783	0.990	0.080
AT5	0.753	0.807	1.018	1.113	0.154
AT6	0.497	0.733	0.792	0.988	0.145
IT2	1.252	1.072	1.583	1.444	0.147
IT3	0.861	0.812	1.148	1.131	0.168
IT4	1.079	0.928	1.316	1.277	0.172

Source: Author (2024)

APPENDIX C : Mediation analysis output

Table 23:Mediation Variance Explained

R-Squared	R^2
ITMEAN	0.353
CHMEAN	0.230

Source: Author (2024)

Table 24: Total Effects

Direct effects								95% Confidence Interval	
			Std. estimate	Std. error	z-value	p-value		Lower	Upper
ATMEAN	→	ITMEAN	0.529	0.059	8.922	0.000		0.406	0.642

Source: Author (2024)

Table 25: indirect effects

Indirect effects									95% Confidence Interval	
					Std. estimate	Std. error	z-value	p-value	Lower	Upper
ATMEAN	→	CHMEAN	→	ITMEAN	0.056	0.028	2005	0.045	0.009	0.123

Source: Author (2024)

Table 26: Mediation path coefficients

Path coefficients							95% Confidence Interval	
			Std. estimate	Std. error	z-value	p-value	Lower	Upper
CHMEAN	→	ITMEAN	0.118	0.058	2.013	0.044	0.005	0.237
ATMEAN	→	ITMEAN	0.529	0.059	8.922	0.000	0.406	0.642
ATMEAN	→	CHMEAN	0.480	0.081	5.923	3.153×10^{-9}	0.336	0.638

Source: Author (2024)