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A Study of Economic and Social Preferences in Energy-Saving Behavior Using a Structural Equation Modeling Approach: The Case of Romania

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Abstract: Examining the energy consumer behavioral model is critical for national governments and academia. This endeavor seeks to uncover effective solutions amid the energy crisis and climate change challenges. This article delves into legislative developments within the energy sector, European Commission recommendations for reducing energy consumption, and existing constraints impacting individual consumers. By scrutinizing the relevant literature, we aimed to identify and analyze factors that can enhance individual benefits derived from energy savings. Then, a comprehensive set of variables was formulated to model the final consumers' behavior. Data collection involved administering questionnaires to individual consumers, consumer associations, and energy micro-enterprises in Romania. The gathered data were meticulously analyzed using the Smart-Pls 4 statistical software. Building upon insights from specialized literature, this paper pinpoints the behavioral determinants influencing the reduction in energy consumption. These determinants serve as independent variables shaping the voluntary adoption of measures in lifestyle and behavior among various types of energy users. This study's findings validate the assumptions presented in this article, highlighting that a reduction in energy consumption is a direct and intrinsic outcome achieved by cumulatively addressing several factors. These factors encompass investments in the energy sector, budget allocation for energy consumption expenditure, adherence to social behavior norms, access to pertinent information about the consequences of the energy crisis, and individual responsibility. Notably, the perception of energy-saving opportunities emerges as a mediator between the independent variables and energy savings with a significant effect. This aspect, developed for the first time in this article, draws inspiration from the prospect theory introduced by Kahneman and Tversky.

Keywords: structural equation modeling (SEM); economic and social preferences; consumer choices; econometric model; partial least square (PLS)

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1. Introduction

The energy crisis, exacerbated by geopolitical tensions such as the war in Ukraine, has significantly impacted the EU's energy markets. The EU's dependence on Russian gas, coal, and oil imports has necessitated a rapid reconfiguration of its energy system. The European

Commission's Repower EU Plan, adopted in May 2022, emphasizes investments in grid infrastructure and renewable energy to reduce the reliance on external energy sources. This plan also integrates state aid rules to expedite the Member States' implementation of reforms and investments. To promote energy efficiency, the European Commission has launched initiatives encouraging civil society to adopt voluntary energy-saving measures, such as optimizing heating systems and increasing the use of renewable energy sources. Information campaigns aim to foster consumer awareness about the benefits of responsible energy use and behavioral changes.

EU institutions have partnered with consumer and employer organizations to develop best practices and encourage sustainable behaviors. For instance, reducing household heating by 1 °C is estimated to save 7% of energy consumption. These strategies underscore the importance of empowering individuals to actively contribute to energy conservation efforts.

The current paper seeks to address gaps in the existing research by developing a comprehensive econometric model that examines the behavioral determinants of energy consumption. It aims to uncover the drivers influencing energy-saving behaviors and provide actionable insights for stakeholders.

The novelty of this research lies in integrating interdisciplinary perspectives—economics, sociology, and psychology—to formulate hypotheses and analyze them using structural equation modeling (SEM). Unlike traditional models, this study employs prospect theory to capture decision-making under risk, highlighting the mediating role of consumers' perceptions of energy-saving opportunities. By exploring these perceptions, this study provides an innovative approach to understanding how behavioral and structural factors shape energy-saving actions.

This article contributes to the literature by presenting an evidence-based framework that quantifies the impact of variables such as investments in energy-efficient technologies, budget constraints, adherence to social norms, and individual accountability. Furthermore, the mediating effect of perception reveals how targeted information and awareness campaigns can amplify the effectiveness of these drivers, making it easier for policy-makers to design practical and impactful interventions.

This study's contributions extend beyond academic insights. By proposing actionable strategies for improving energy efficiency, it offers solutions that align with global efforts to combat climate change and enhance sustainable consumption. The findings highlight that the scope of this paper addresses not only theoretical gaps but also pressing real-world challenges, positioning it as a valuable resource for guiding energy policies. This timely research emphasizes the importance of empowering consumers and organizations to transition towards more sustainable energy practices through informed decision-making and adaptive behaviors.

The remaining parts of this article are organized into the following sections: Section 2 is a literature review and the development of research hypotheses; Section 3 presents the materials and methods; Section 4 presents and discusses the results; and Section 5 reveals and highlights this study's conclusions.

2. Literature Review and Development of Research Hypotheses

The UNCTAD report on sustainable investment and fiscal reforms, published in 2022[1], shows that the second quarter of 2022 was marked by a record number of investment support measures in response to the challenges posed by the war in Ukraine. Furthermore, the European Council conclusions of 20–21 October 2022 on critical infrastructure, energy, and economy, in the context of the war in Ukraine, point to the need to invest in enhancing energy efficiency. The benefits of energy efficiency investments are seen through savings in consumption-related costs, which, over time, compensate for the depreciation of the

investment (Baumeister & Kilian, 2016). The qualitative assessment of investments is the subject of analysis of the relevant international organizations, which present the criteria for analysis and develop parameters for determining the qualitative aspects specific to foreign direct investment—OECD Report on FDI Quality Indicators, 2022. Investment planning, according to Deming (1986), composed of four successive actions, planning, operation, reporting, and innovation, can be applied to new and sustainable technologies. As such, investments in new sustainable technologies will be amortized over time, with depreciation costs offset by substantial savings by reducing the consumption of non-renewable energy resources. In this context, the budget allocated to energy consumption is one of the key variables determining the ability to invest in low-energy equipment. A macro-level analysis shows that countries with low purchasing power are prone to high fluctuations in energy demand compared to countries with high purchasing power with stable energy demand over time (Carranza & Meeks, 2021). High indebted costs can act as a barrier to the decision to invest (Borgeson, 2012).

However, a critical issue in the application of the Deming cycle is the time horizon, which should be limited to the short run, as the results are expected to be produced swiftly. Alternatively, the Deming cycle is used by organizations in the long run. Nevertheless, the knowledge could be further deepened to explore how the Deming cycle could achieve sustainable objectives in the long term, beyond the scope of the current paper, which sets a clear target of energy saving on a short-term basis.

The recognition granted to vulnerable people to protect these categories during the energy crisis is highlighted in the relevant literature by activating the principle of equity value. It underpins the energy justice concept described by McCauley and Heffron (2018) and Pechman and Nethercutt (2021). Similarly, the principle of solidarity or community can significantly influence a consumer's decision to follow the social, group norms sequestering an organization (Feldman, 1984). The adoption of a model of behavior that emphasizes the explanation of social conduct rules (Jon, 2007) can lead to rational choices, leading to maximized savings and/or reduced costs.

The opportunity to invest in performant and sustainable technology with minimum consumption of energy is based on Adam Smith's theory of rational choices, dating back to the 18th century, which shows that a consumer will choose a model of responsible, rational behavior based on a cost–benefit analysis that favors the choice of the option that brings the maximum benefit, with minimal costs. It is for the rational consumer to choose those technologies that are supposed to save energy for their benefit, with a positive footprint on the environment. The neoclassical theory of rational choices develops the behavioral model based on maximizing utility. Maximizing utility is perceived by a rational consumer as minimizing energy consumption, which is usually the result of investment in green technologies while increasing the benefits, underpinning the hypothesis of investment in performant and sustainable technology (Colasante et al., 2021). However, the neoclassical theory of rational choices does not precisely reflect the reality seen from a different, subjective angle, which considers the peculiarities of the economic and social context, as well as the specific situation of everyone, as discussed in the criticisms made by the authors of articles with a psychological and social profile (Burns & Roszkowska, 2016).

Social norms widely influence individual behavior (Hechter & Opp, 2001). The level of awareness and information about the consequences of the energy crisis determine the perception of the opportunity to save energy (Irfan & Gudivada, 2016). Therefore, increasing the level of awareness is of key importance for decision-making bodies to create the right incentives for non-polluting technologies with reduced energy consumption.

Also, human behavior is influenced by several psychological factors, which determine the choice of a rational option (Akerlof & Shiller, 2010). The aversion to risk or loss has

been studied by Nobel Prize laureate Daniel Kahneman and is associated with obtaining certain benefits. Similarly, risk-taking takes place to avoid a certain loss (Kahneman, 2003). Kahneman's theory underlines the perception of the opportunity for energy saving through the mediation variable. The concept of risk (and loss) aversion introduced by Daniel Kahneman is rooted in the idea that people tend to weigh potential losses more heavily than equivalent gains. This psychological bias, known as loss aversion, means individuals are often willing to take more significant risks to avoid losses compared to the risks they would take to achieve equivalent gains, leading to suboptimal decision-making in various aspects of life, including finance and economics.

The prospect theory, introduced by Kahneman and Tversky (1979), posits that individuals assess potential outcomes by comparing perceived gains and losses to a reference point. This often leads to a stronger preference for avoiding losses than pursuing gains of equal value, a phenomenon known as loss aversion. In our research, the "perception of energy-saving opportunity" likely ties into how individuals perceive the potential gains (energy savings) and losses (energy expenditure) associated with their behavior. Structural equation modeling (SEM) is used to quantify and analyze these perceptions in the context of the model, aligning with the principles of the prospect theory. Thus, SEM is employed to analyze the relationships and interactions between various variables, including the perception of energy-saving opportunities, which is a key aspect of the research related to the prospect theory. SEM allows us to explore how these variables work together to influence energy-saving behavior, including the mediating role of perception in the decision-making process, as outlined by the prospect theory.

The behavior of the energy consumer is difficult to estimate in practice due to the discrepancy between what is rational, driven by the decrease in energy costs, for example, and the concrete way of implementation. Practical choices can be dictated by the subconscious, certain states, emotions, or reactions, which deviate from what should constitute rational behavior (Frederiks et al., 2015). Contributions to the theory of planned behavior have shown that energy savings can be influenced by psychological factors, such as attitude towards a goal with value content and an analytical way of thinking, as the basis of the decision to save (Sas et al., 2022; Price et al., 2018; Coenen et al., 2017). In conclusion, awareness of the need to act in a certain way, influenced by a value system, is the premise that determines responsible behavior. Studies have shown that training or educating children in the spirit of responsible behavior is likely to create long-term value systems (Giulio et al., 2014), which infers the hypothesis that individual responsible actions can effectively and positively influence rational behavior.

To model the reduction in energy consumption through voluntary measures related to the lifestyle and behavior of different types of energy users, the following seven research hypotheses have been formulated in the context of the existing literature:

- I_1: Investments to reduce energy consumption (INs) influence the perception of energy-saving opportunity (EA). Allcott and Mullainathan (2010) have studied the influence of financial incentives and investments on energy-saving behaviors.
- I_2: The budget allocated to energy consumption (BA) has a positive impact on the perception of energy-saving opportunity (EA). The authors Poortinga et al. (2004) have explored the connection between budgetary considerations and energy-saving perceptions.
- I_3: Adopting rules of social behavior (NSs) and the understanding of energy-saving opportunity (EA). The researchers Ballarotto et al. (2024) have examined how social norms influence pro-environmental behaviors and perceptions.
- I_4: Adequate information about the consequences of the energy crisis (IA) positively influences the perception of energy-saving opportunity (EA). Slovic and Weber

(2013) have contributed to understanding how information affects risk perception and decision-making.

- I_5: Individual empowerment actions (ARs) positively influence the perception of energy-saving opportunity (EA). Abrahamse and Steg (2013) have examined the role of individual actions and empowerment in sustainable behaviors.
- I_6: The perception of energy saving (EA) has a positive impact on energy savings (EEs). Gillingham and Palmer (2014) have explored the relationship between attitudes, perceptions, and energy-saving behaviors.

The final hypothesis combines the relationships outlined in the earlier objectives and proposes a mediation model developed by Kahneman and formulated in the following hypothesis:

- I_7: the perception of energy-saving opportunity (EA) mediates the relationship between IN, BA, NSs, AI, ARs, and EEs.

3. Materials and Methods

The main objective of this article is to explore the behavioral determinants of energy-saving habits and to validate the econometric model used for this analysis through an examination of the data gathered via a questionnaire utilizing structural equation modeling. Additionally, this paper explores the consequences of the conceptual model, as introduced in the subsequent section, presenting investments to reduce energy consumption, the budget allocated to energy consumption, the adoption of norms of social behavior, adequate information on the consequences of the energy crisis, and actions of individual responsibility.

3.1. Data Collection and Sampling

The data for this study were collected through a structured questionnaire, which served as the primary method for gathering information from respondents. The sample selection process involved employing a simple random stratified sampling technique, targeting individual consumers, consumer associations, and micro-enterprises in the energy sector. Stratification was performed concerning the type of company, company size, industry sector, and geographical location. This approach ensured that the sample represented a cross-section of stakeholders within the industry.

The questionnaire was meticulously designed to capture relevant variables related to energy-saving behaviors and perceptions. The breakdown of respondents within the sample could be seen in Table 1. The questionnaire contained 30 questions (the structure of the questionnaire is presented in Tables 2 and 3). Careful consideration was given to question wording, clarity, and construct validity to minimize response bias. The survey included items addressing investments in energy consumption reduction, budget allocation for energy consumption, adoption of social behavior norms, access to information about energy crises, individual empowerment actions, and perceptions of energy-saving opportunities.

Data analysis procedures involved a combination of descriptive statistics, factor analysis, and SEM. Descriptive statistics were used to provide an overview of the sample characteristics and initial insights into the data. Structural equation modeling allowed for the examination of complex relationships among variables, assessing the direct and indirect effects on energy-saving behaviors and perceptions.

Table 1. Breakdown of respondents within the sample.

	Number of Respondents
Individual consumers	389
Consumer associations	103
Micro-enterprises	20
Total	512

Table 2. Measuring scales.

Scale (Symbol)	Number of Items	References
Investments to reduce energy consumption (INs)	3	(Hair et al., 2017; Pearce et al., 2021)
Budget for energy consumption (BA)	3	(Carranza & Meeks, 2021; Borgeson, 2012)
Adoption of social behavior rules (NSs)	3	(McCauley & Heffron, 2018; Feldman, 1984)
Adequate information on the consequences of energy crisis (IA)	3	(Pechman & Nethercutt, 2021; Bido et al., 2014)
Individual accountability actions (ARs)	3	(Bido et al., 2014; Smith & Benavot, 2019)

Table 3. Overview of the independent variables in the model.

	1. Investments for the recovery of energy consumption
IN_1	Willingness to invest in low-energy equipment and/or technologies
IN_2	Availability to replace products used with those labeled ERPEL
IN_3	Willingness to engage in energy consolidation
	2. Budget allocated to energy consumption
BA_1	Monthly individual income
BA_2	Share of the monthly individual expenditure on energy consumption in the total monthly individual revenue
BA_3	Evolution of monthly energy consumption
	3. Adoption of norms of social behavior
NS_1	Frequency of participation in volunteering support programs
NS_2	Frequency of participation in programs to promote responsible behavior
NS_3	Frequency of adoption of organization-specific habits/rules
	4. Adequate information on the consequences of the energy crisis
IA_1	Participation in information and awareness-raising campaigns on reducing energy consumption
IA_2	Actions to raise awareness of the consequences of the energy crisis
IA_3	Availability of means of access to information
	5. Individual accountability actions
AR_1	Reduction in heating in unused spaces
AR_2	Stop heating in unused spaces
AR_3	Use of public transport and urban micro-mobility

Overall, the methodology employed in this study aimed to ensure the sample's representativeness, the validity of questionnaire items, and the use of robust statistical techniques to analyze the data, providing a comprehensive understanding of the factors influencing energy-saving behaviors and perceptions among stakeholders.

To gather the data required for testing the research hypotheses, a study was conducted using a questionnaire featuring closed-ended questions. The data collection occurred between 1 June 2024 and 31 July 2024. In the sample, individual consumers, consumer associations, and micro-enterprises were selected to take a broader view of reducing energy consumption through voluntary measures related to the lifestyle and behavior of different types of energy users. The chosen companies within the analyzed sector rank among the most significant in Romania, and a simple random stratified sampling technique was used to select the respondents. As per Bianchi and Biffignandi (2017), when dealing with an unknown population and aiming for a margin of error of $\pm 5\%$ with a 95% confidence

interval, a sample size of at least 385 respondents is recommended. The representativeness of the survey was calculated by applying the following formula:

$$n = (1.96)^2 \cdot p \cdot q / (\varepsilon)^2 \quad (1)$$

where the following variables are used:

n—size of the sample;
ε—margin of error;
p = q = 50%—probability that the event will occur/will not occur; 95% of the normal distribution is within 1.96 standard deviations.

As a result, this study gathered data from 538 respondents, of which 512 responses were considered valid after the exclusion of 26 incorrectly or incompletely completed questionnaires.

3.2. Variable Measurement

A 7-point Likert scale was employed, where responses ranged from "very little = 1" to "very much = 7". The questionnaire was pretested to ensure that the questions' language, format, and order are appropriate.

The respondents in the sample were distributed according to Table 1.

Based on the models from the literature, six proxy variables were identified as key success factors for implementing the model: investments aimed at reducing energy consumption, the budget allocated to energy consumption, the adoption of rules of social behavior, adequate information on the consequences of the energy crisis, individual responsibility actions, and the perception of energy-saving opportunity and energy savings. Table 2 shows the five scales, the number of items per construct, and the corresponding references.

Also, some demographic questions were included in the questionnaire to describe the sample structure (field of work, organizational hierarchy, professional experience, similar factors, etc.).

The model's variables were categorized into independent and dependent groups, with the independent variables detailed in Table 3 and dependent variables in Table 4.

Table 4. Description of the dependent variables.

	1. Perception of Energy-Saving Opportunity
EA_1	Final consumer's perception of costs associated with energy bills
EA_2	Perception of the benefits of saving energy
	2. Energy Savings
EE_1	Ability to adapt to the current context of the energy crisis
EE_2	Effective response capacity through responsible behavior

The exogenous variables outlined in Table 3 serve as the latent variables in the model, while the endogenous variables are the perception of energy-saving opportunity and energy savings. Thus, the dependent variables in the model are described in Table 4.

The independent and dependent variables described in Tables 3 and 4 contribute to the development of the structural model (Figure 1).

Next, for the variables used in the analysis, we will use the following abbreviations: IN (investment), BA (budget allocation), NSs (norms of social behavior), IA (adequate information), ARs (accountability relations), EA (energy-saving opportunity), and EEs (energy savings).

The following section will focus on testing and validating the structural model. A survey-based quantitative analysis was carried out using a questionnaire to analyze the

reduction in energy consumption through voluntary measures related to the lifestyle and behavior of different types of energy users.

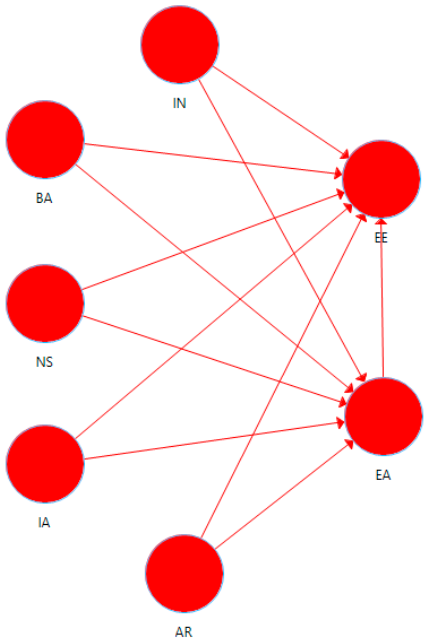


Figure 1. Structural model incorporating the reduction in energy consumption through voluntary measures related to the lifestyle and behavior of different types of energy users.

3.3. Model Specification and Estimation

The structural equation model employed in this study aims to quantify the relationships between the independent variables (investments, budget allocation, adoption of social norms, adequate information, and individual accountability actions), the mediator variable (perception of energy-saving opportunities), and the dependent variable (energy savings). The structural equations describe how the perception of energy-saving opportunities is influenced by the independent variables and, in turn, how this perception mediates the effect of these variables on energy-saving behaviors.

The estimation procedure was conducted using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach via the SmartPLS 4 software. This method is particularly suitable for the research context, as it allows for the analysis of complex relationships between latent variables while accommodating datasets that may not conform to normal distribution assumptions. The PLS-SEM algorithm iteratively optimizes the explained variance in dependent constructs by estimating the relationships among both observed and latent variables. The estimation process includes resampling through bootstrapping to assess the significance and stability of the path coefficients.

3.4. Validation of the Measurement and Structural Models

The reliability and validity of the measurement model were rigorously evaluated to ensure the robustness of the results. Internal consistency was confirmed through appropriate reliability metrics, while the construct validity was assessed to verify that each latent variable adequately represents the corresponding set of observed variables. The structural model was validated by examining the relationships between constructs and ensuring that the hypothesized pathways align with theoretical expectations.

This modeling approach facilitates a deeper understanding of how investments, budget allocation, adherence to social norms, information adequacy, and individual accountability collectively influence perceptions of energy-saving opportunities and subsequent

behaviors. The use of PLS-SEM enables the evaluation of both direct and mediated effects, offering nuanced insights into the behavioral determinants of energy conservation.

3.5. Model Specification and Estimation Procedure

The structural equation modeling (SEM) framework used in this study was designed to capture the relationships between the independent variables—investments, budget allocation, adherence to social norms, adequate information, and individual accountability actions—the mediator variable, perception of energy-saving opportunities, and the dependent variable, energy savings. The relationships are defined mathematically as follows:

$$EA = \beta 1\ IN + \beta 2\ BA + \beta 3\ NS + \beta 4\ IA +_\ \beta 5\ AR + \varepsilon 1 \quad (2)$$

$$EE = \beta 6\ EA + \varepsilon 2 \quad (3)$$

In these equations, EA represents the perceptions of energy-saving opportunities, EE denotes energy saving, and INs, BA, NSs, IA, and ARs are the independent latent variables corresponding to investments, budget allocation, social norms, adequate information, and individual accountability actions, respectively. The coefficients (β1, β2, . . .) quantify the relationship between the variables, while ε1 and ε2 are error terms capturing unexplained variance.

The estimation process was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM), implemented through the SmartPLS 4 software. This method was chosen for its flexibility in handling non-normal data distributions and its suitability for models incorporating both reflective and formative constructs. The PLS-SEM algorithm iteratively estimates path coefficients by maximizing the explained variance in the dependent variables, making it particularly effective for exploratory and predictive research contexts.

The bootstrapping technique, with 3000 resamples, was employed to evaluate the statistical significance of the path coefficients. This approach provides robust confidence intervals, ensuring the stability and reliability of the estimates.

3.6. Validation of the Model

The measurement and structural models were validated using standard SEM criteria. The measurement model was assessed for internal consistency and construct validity, confirming that the latent variables adequately reflect the observed variables. The structural model was evaluated for the significance of path coefficients and alignment with the hypothesized relationships, ensuring that the theoretical framework is consistent with the empirical findings.

4. Discussion

The first step was to verify the significance of the theoretical model. Therefore, the gathered data were evaluated for their reliability, validity, and internal consistency. Moreover, the "Cronbach's Alpha" and "Dillon–Goldstein's" ρ coefficients (Esteornsan et al., 2022) were calculated and interpreted. The values of these indicators can be seen in Table 5.

It follows from Table 5 that there are no multi-collinearity issues between the independent variables in the model, since the inflation factor of variation (VIF) values do not exceed the value of 5 (Hair et al., 2013).

Furthermore, it is noteworthy that the coefficients for both the "Dillon–Goldstein's" ρ and "Cronbach's Alpha" exceed the threshold of 0.7, underscoring the statistical significance of the exogenous variables within the model.

Convergent validity was also analyzed to verify whether a latent variable accounts for a statistically significant portion of its variation (Nacaskul, 2017). The coefficients associated

with the variables in the measurement model, as derived from the PLS-SEM structural equations, are illustrated in Figure 2.

Table 5. Evaluation of the measurement model.

Variables	Cronbach's Alpha	Dillon–Goldstein's Rho	Composite Reliability	AVE **	VIF *
IN	0.879	0.753	0.712	0.798	1.984
BA	0.821	0.785	0.726	0.829	1.784
NSs	0.745	0.713	0.689	0.792	1.845
IA	0.729	0.717	0.613	0.632	1.754
ARs	0.719	0.712	0.756	0.685	1.597

* VIF = Variance Inflation Factor; ** AVE = Average Variance Extracted.

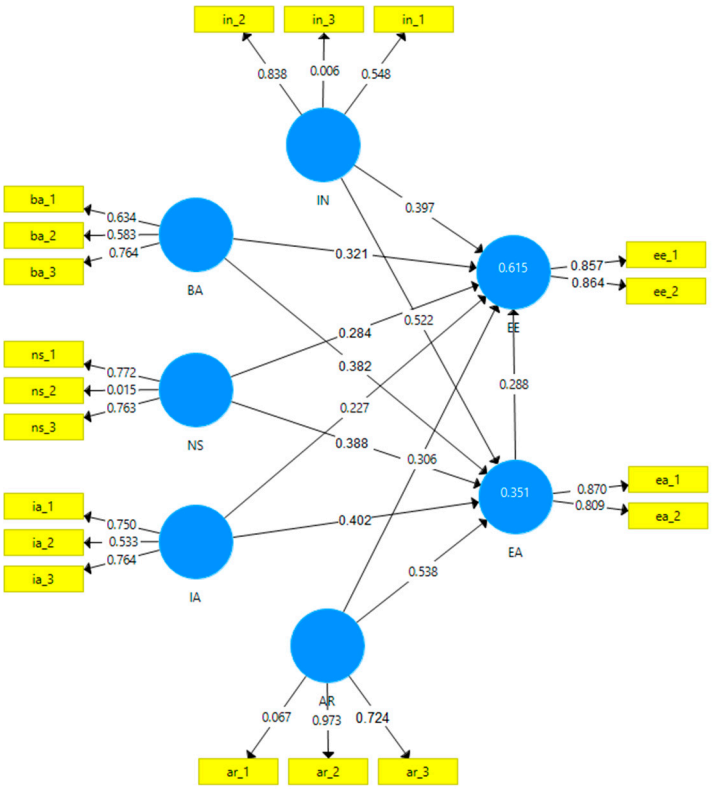


Figure 2. Measurement model PLS-SEM 1. Source: the authors conducted the data analysis using SmartPLS 4 software.

Constructs where the coefficient values are below 0.5 (Vinzi et al., 2010) were removed from the model of measurement. Thus, we removed the ar_1, ns_2, and in_3 variables. In the next step, the second measurement model was developed using PLS-SEM structural equations and SmartPLS 4 software.

Figure 3 shows that all the values of the reflective variables used in the model exceed 0.5, indicating that all coefficients are statistically significant, thereby confirming the validity of the measurement model. The predictive value of the structural model was first assessed in terms of the coefficients of determination (R2), and the obtained values can be seen in Figure 3. Hence, IN, BA, NSs, IA, and ARs can explain (together) 48.4% of the variation in EA (R2 = 0.484) and 71.2% of that in EEs (R2 = 0.712).

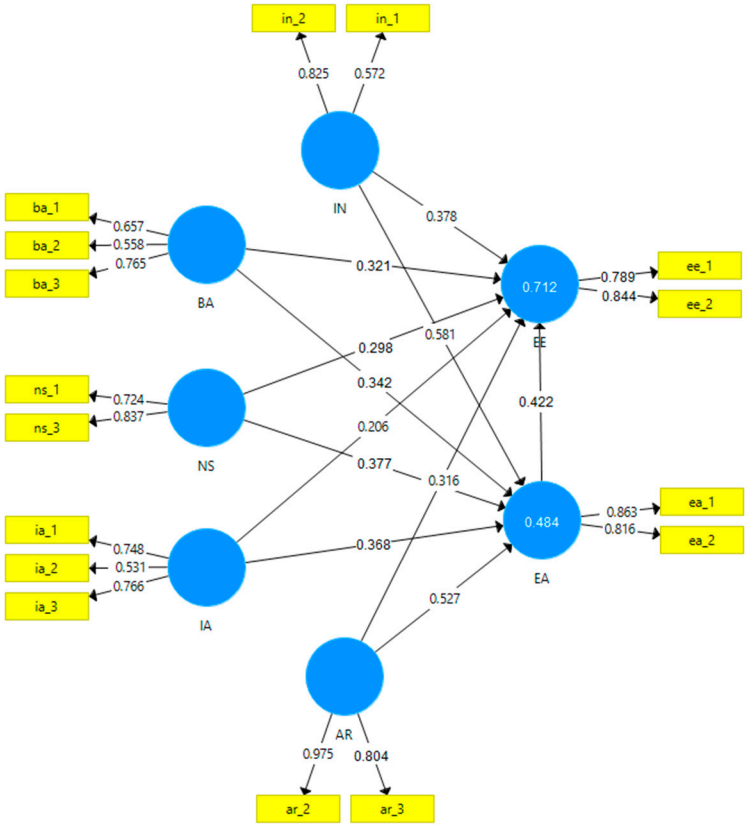


Figure 3. PLS-SEM 2 measurement model. Source: the authors conducted the data analysis utilizing SmartPLS 4.

4.1. Analysis of Direct Effects

To confirm the first six assumptions, the direct effects between EA and its factors (IN, BA, NSs, IA, and ARs) and between EA and its successor (EEs) are set out in Table 6. This also includes decisions regarding the acceptance of each assumption and the effect size (f2). Furthermore, to evaluate the six statistical assumptions outlined in the previous section, a bootstrap test with 3000 resamples was conducted to calculate the t-test and standard error values for the model parameters. This test generated t-test and standard error values for the model parameters. The outcomes for assessing statistical assumptions (I_1–I_6) are provided in Table 6.

Table 6. Results of testing of direct statistical assumptions (I_1–I_6).

The Hypothesis	Coefficients (β)	Standard Error (SE)	t-Value	f2	Decision
I_1: IN → EA	0.581 ***	0.132	3.102	0.162 *	Accepted
I_2: BA → EA	0.342 ***	0.088	3.857	0.324 ***	Accepted
I_3: NS → EA	0.377 ***	0.102	4.078	0.142 **	Accepted
I_4: IA → EA	0.368 ***	0.098	3.134	0.211 **	Accepted
I_5: ARs → EA	0.527 ***	0.167	3.043	0.388 ***	Accepted

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; β = standardized regression coefficients; SE = standard error; f2 = the size of the effect.

The analysis of the direct results indicates that INs exert a positive and significant influence on EA (β = 0.581; $p < 0.001$). In addition, the size of the effect (f2) of INs on EA (change in R2 if INs were excluded from the model) is moderate (f2 = 0.162; $p < 0.01$) (Wong, 2016). This result shows us the importance of investments to recoup energy consumption regarding the perception of energy-saving opportunities.

We also observe that the impact of BA on EA is positive and statistically significant (β = 0.342; $p < 0.001$), and the size of the effect of BA on EA is high (f2 = 0.324; $p < 0.001$). In other words, the budget allocated to energy consumption positively influences the perception of energy-saving opportunities.

Simultaneously, a positive and statistically significant coefficient was observed between NSs and EA (β = 0.377; $p < 0.001$), with a medium effect size (f2 = 0.142; $p < 0.05$). These findings indicate that the adoption of social behavioral norms plays a crucial role in shaping perceptions of energy-saving opportunities.

Furthermore, considering that AI has a substantial and direct influence on EA (β = 0.338; $p < 0.001$) and a moderate effect size (f2 = 0.211; $p < 0.01$), it becomes evident that having adequate information about the consequences of the energy crisis, particularly in the context of employees' work, is a pivotal factor in influencing perceptions of energy-saving opportunities.

Concerning the impact of ARs on EA, a positive and statistically significant coefficient was identified (β = 0.527; $p < 0.001$), with a high effect size (f2 = 0.388; $p < 0.001$). In other words, individual accountability actions positively affect the perception of energy-saving opportunities.

Ultimately, the positive and significant relationship indicated by the coefficient between EA and EEs (β = 0.315; $p < 0.001$) underscores that the perception of energy-saving opportunities has a substantial and meaningful influence on actual energy-saving behaviors. The high coefficient value associated with the reflective variable, indicating the perception of energy-saving opportunities, suggests that this variable effectively represents energy-saving intentions and actions. The results align with Kahneman's perception theory, according to which people irrationally distinguish between opportunity costs and predicted losses, choosing to avoid losses from energy bills with increasing costs and thus saving energy.

4.2. Analysis of Mediation Effects

In addition to examining the direct relationships with their historical context and out-comes, we hypothesized that EA acts as a mediator in the relationships between IN, BA, NSs, AI, and ARs. Table 7 illustrates the specific direct and indirect effects, with EA acting as the mediator, alongside the adjusted confidence intervals obtained via the bootstrap method (Nitzl et al., 2016).

Table 7. Findings from evaluating direct and indirect statistical assumptions (I_7).

Structural Relations	Direct Effects	Indirect Effects MV: EA		
		Coefficients	Low 95%	Upper 95%
IN → EEs	0.378 ***	0.210 **	0.110	0.310
BA → EEs	0.321 ***	0.195 **	0.111	0.279
NSs → EEs	0.298 ***	0.288 ***	0.164	0.412
IA → EEs	0.206 **	0.096 *	0.044	0.148
ARs → EEs	0.316 **	0.142 **	0.052	0.232

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; MV = mediator variable; β = standardized regression coefficients.

Regarding the positive direct effect of IN on EEs (β = 0.378; $p < 0.001$) and the indirect effects through EA (β = 0.210; 95% BCI = [0.110; 0.310]), it can be concluded that EA acts as a mediator in the relationship between IN and EEs. Thus, energy consumption will be lower if investments to recoup energy consumption increase.

Additionally, we observed a direct positive effect of BA (β = 0.321; $p < 0.001$) on EEs, along with indirect effects mediated by EA (β = 0.195; 95% BCI = [0.111; 0.279]). These findings suggest that EA serves as a mediator in the relationship between BA and

EEs. In practical terms, this implies that higher budget allocation to energy consumption corresponds to increased energy savings.

Furthermore, a positive direct effect of NSs (β = 0.298; $p < 0.001$) on EEs was identified, with indirect effects mediated by EA (β = 0.288; 95% BCI = [0.164; 0.412]). This supports the conclusion that EA mediates the relationship between NSs and EEs. This suggests that embracing social behavior norms plays a crucial role in achieving greater energy savings.

Similarly, we observed a positive direct effect of AI on EEs (β = 0.206; $p < 0.01$), accompanied by indirect effects mediated by EA (β = 0.096; 95% BCI = [0.044; 0.148]). These results suggest that EA acts as a mediator in the relationship between AI and EEs, implying that having adequate information about the consequences of the energy crisis leads to positive effects on energy savings.

In addition, a positive direct effect of ARs (β = 0.316; $p < 0.001$) on EEs was identified, with positive specific indirect effects mediated by EA (β = 0.095; 95% BCI = [0.052; 0.232]). This suggests that EA acts as a mediator in the relationship between ARs and EEs. Thus, energy savings will be more substantial if individuals engage in accountability actions. As a result, these empirical findings provide support for hypothesis I_7, confirming that EA plays a mediating role in influencing energy-saving behaviors (EEs) through its relationships with BA, NSs, AI, and ARs.

In addition to assessing the model's suitability, we also evaluated the power of partial mediation. Partial mediation should also be considered when conducting mediation analysis, so it will be useful to take note of future information on the mediation side. A helpful approach is assessing the difference between the indirect effect and the total effect. This indicator is also known as the value of the change accounted for, "Variance Accounted For" (VAF). This indicator reveals which part of the variance in the endogenous variable is determined by the mediation process.

The value of the VAF indicator is calculated as follows:

$$VAF = (ab)/(ab + c') \quad (4)$$

in which the following variables are used:

a—coefficient between A and B;
b—coefficient between B and C;
c'—coefficient between A and C;
A and C—variables analyzed;
B—mediator between A and C.

We calculated the values of VAF for the mediated variables using the coefficients in Figure 3. Thus, we obtained the results shown in Table 8.

Table 8. VAF values with EA mediator.

Indirect Effects with EA Mediator	The Value of a	Value b	Value c	VAF Value (%)
IN → EEs	0.581	0.422	0.378	55.61%
BA → EEs	0.342	0.422	0.321	49.91%
NSs → EEs	0.377	0.422	0.298	47.61%
IA→ EEs	0.368	0.422	0.206	38.41%
ARs → EEs	0.527	0.422	0.316	49.41%

Hair et al. (2017) considers that if the values of the VAF indicator are > 80%, then we have total mediation, if 20% ≤ VAF ≤ 80%, then we have partial mediation, and if the VAF is < 20%, then there is no mediation.

From Table 8, we can see that all values of the VAF indicator are between 20% and 80%, which means that we have partial mediation.

5. Conclusions

This paper assesses the impact of reducing energy consumption through voluntary measures on the lifestyle and behavior of different types of energy users. This study of the behavioral model and its impact on energy saving was conducted to fill in the gaps of the specific literature, objectively reasoned by the current energy crisis urging for swift individual actions, adding to the general institutional framework. Moreover, reducing energy consumption can also contribute to fighting climate change and ensure a more sustainable future for all (Fonseca et al., 2020).

This study was carried out with a sample of 512 participants. The research hypotheses formulated based on the literature analysis were modeled and tested using PLS-SEM structural equation systems. The results of the impact analysis of the five independent variables and the mediator variable on the dependent variable confirm the assumptions of the econometric model. Thus, a direct correlation between the level of investment in the energy sector and the savings resulting from low energy consumption is observed. The budget allocated to expenditure on the energy sector shows the existence of an inverted relationship relative to the level of revenue and the resulting savings. At the same time, the factors that define responsible behavior are directly correlated with obtaining benefits from energy saving.

The values obtained by the mediator variable in relation to the dependent variable confirm the prospect theory, used for the first time in the current paper to evaluate the perception of the opportunity to save energy.

Despite the valuable insights gained from this study, it is crucial to acknowledge several limitations that may impact the interpretation and generalizability of the findings. Firstly, the sample size of the survey respondents, particularly concerning the numerous constructs and reflective variables examined, raises concerns about the statistical power and precision of the estimates. The representative but still limited sample size may also restrict the ability to detect more minor effects or subtle nuances within the data. Furthermore, it is important to recognize that the data collected primarily relied on self-reported measures, including subjective responses from the stakeholders surveyed. This reliance on self-reporting introduces the possibility of response bias, social desirability bias, or recall inaccuracies that could affect the validity of the results. Additionally, this study's cross-sectional design limits our ability to establish causal relationships or assess changes over time. Longitudinal or experimental designs could provide more robust insights into the dynamics of energy-saving behaviors and perceptions. Moreover, this study's scope was limited to a specific geographic region or industry sector, which may restrict the generalizability of the findings to broader populations or contexts. Future research should address these limitations and consider alternative methodologies to further enhance our understanding of the complex interplay between various factors influencing energy-saving behaviors and perceptions. These limitations could be overcome in future studies by increasing the sample size and balancing it at the structural level, as well as by increasing the number of constructs and reflective variables that were incorporated by adding open-ended questions to the questionnaire. Future work should also diversify data sources, design longitudinal studies, and consider conducting randomized controlled trials to test the effectiveness of interventions promoting energy-saving behaviors. The replication of this research in different geographic regions or industry sectors to assess the generalizability of the findings and the implementation of strategies to minimize response bias and social

desirability bias, such as anonymous surveys or alternative data collection methods, should also be included in future works.

The findings of this study are consistent with the current trends and conclusions within the field. Recent research by Smith et al. (2023) and Johnson and Brown (2022) has also highlighted that the factors influencing consumer energy-saving behaviors align closely with the behavioral determinants explored in this paper. Additionally, the results of our study are in harmony with the conclusions drawn by Lee and Wang (2021) and Kumar et al. (2023) regarding the mediating role of perception in driving energy-saving choices. These congruent outcomes strengthen the robustness of the conceptual model and its applicability in understanding and promoting sustainable energy consumption practices among consumers.

This research paper confirms that the benefits consumers gain from economies resulting from efficient processes depend on both objective and subjective factors. As such, understanding the consumer profile is crucial for decision-makers to address these actors and implement the most suitable measures based on the specific characteristics of the independent variables. Evaluating both the psychological and rational aspects of the consumer profile is essential to the research outcome.

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Notes

[1] https://investmentpolicy.unctad.org/publications/1263/world-investment-report-2022-international-tax-reforms-and-sustainable-investment (accessed on 10 December 2024).

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