"Never let a good crisis go to waste". The Effect of an Energy Crisis on Individuals' Energy Saving Behavior in the Netherlands.

Richt Fokkens (s3048691)

Master thesis

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ABSTRACT

Household energy consumption significantly contributes to greenhouse gas emissions (van der Werff & Steg, 2015). Therefore, it is critical that households reduce their energy (van der Werff & Steg, 2015). The sharply rising cost of electricity and gas motivated many Dutch citizens to make energy-saving changes in their homes (I&O Research, 2022). Past studies often focused solely on internal motivations to measure and predict sustainable behavior, whereas this study contributes by adding external contexts to internal motivation. This was done by using a theoretical framework based on a combination of the Theory of Planned Behavior (TPB) by Ajzen (1991) and the Attitude-Behavior-Context model by Stern and Oskamp (1987). Data was collected using an online self-reported survey. The target group concerned the general Dutch population (N = 233) with a requirement of being over 18 years old. Structural Equation Modeling (SEM) was used for testing understanding which factors are influencing an individual's energy-saving behavior (Hair et al., 2014). The study's findings indicated that intention to save energy was a poor predictor of energy-saving behavior. In terms of TPB, the study found that Attitude was considered to be the strongest predictor of both Intention and Behavior. The additional factors Subjective Norm was a weak predictor of energy-saving behavior, and Perceived Behavioral Control did not appear to be a predictor at all. The external factors Positive Context and the Negative Context both demonstrated a clear correlation with Attitude and Energy Saving Behavior, indicating that they are reliable predictors of such behavior and can be helpful in future studies. An alternative framework was proposed to show which variables influence energy-saving behavior in the Netherlands in times of an energy crisis.

List of abbreviations/tables/figures

Abbreviation	Definition
ESB	Energy Saving Behavior
ESI	Energy Saving Intention
TPB	Theory of Planned Behavior
SN	Subjective Norm
AT	Attitude
PBC	Perceived Behavioral Control
ABC-model	Attitude, Behavior, Context model
PC	Positive Context
NC	Negative Context
SEM	Structural Equation Modeling
MLE	Maximum Likelihood Estimation
MI	Modification Indices
CFA	Confirmatory Factor Analysis

Acknowledgements

A significant challenge for me is contained in the thesis that is presented to you. Although studying sustainable behavior was relatively known to me, this form of analysis (SEM) and adding the presently understudied energy crisis was not. This new experience of quantitative research has provided me with a new perspective on research and added to my previous studies related to (sustainable) energy in the Province of Friesland. To begin with, I would like to express my appreciation to my first supervisor dr. Ewert Aukes and my second supervisor dr. Lisa Sanderink for providing feedback and supporting me during the process. Also, I want to thank my peer MEEM-student Aidin Bayazian for supporting me along the process, and more importantly, for being a wonderful friend. Lastly, I would like to thank my family for always supporting me.

Richt Fokkens

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1. Introduction

1.1 Context

Household energy consumption significantly contributes to greenhouse gas emissions (van der Werff & Steg, 2015). Therefore, it is critical that households reduce their energy consumption (van der Werff & Steg, 2015). Energy saving can be done in a variety of ways, such as using energy-efficient appliances and measures in buildings, embracing renewable energy sources and technologies, and engaging in energy-saving behaviors (Suntornsan et al., 2022). Individual energy-saving behavior has been the subject of extensive research for decades (Abrahamse et al., 2005; Du & Pan, 2021; Gao et al., 2017; Steg, 2008; Sütterlin et al., 2011; Stern, 1999). The majority of research focuses on the willingness and determinants of households to conserve energy (van der Werff & Steg, 2015). Behavioral science such as the studies by Abrahamse & Steg (2011), Du & Pan (2021), and Gao et al. (2017) show that energy saving intentions are positively related to actual energy saving behavior. Moreover, Abrahamse & Steg (2011) showed that socio-demographic variables such as age, household size and income are strongly related to consumption. Frederiks et al. (2015) showed the complexity of energy saving behavior in the field of behavioral economics. Their study found that consumers do not always make fully rational decisions, as standard economic models imply, and that there is often a discrepancy between people's values and their actual behavior. This phenomenon is also known as the 'intention-behavior gap' (Conner & Norman, 2022).

1.2 Research Problem & Knowledge Gap

These studies, however, do not take into account the ongoing energy crisis, which started with the COVID-19 epidemic and has been exacerbated by the war between Russia and Ukraine (Lambert et al., 2022). In the Netherlands, this has resulted in a rapid decline in energy consumption (I&O Research, 2022). According to the I&O Research (2022), Dutch households have adopted more pro-environmental behavior over the years, including the use of energy-efficient heating systems, traveling less by plane and car, consuming less meat, and taking shorter showers (I&O Research, 2022). The sharply rising cost of electricity and gas motivated many households to make energy-saving changes in their homes (I&O Research, 2022). About 80% of Dutch citizens have altered their behavior to reduce their gas and/or energy costs (I&O Research, 2022). Although this sudden decline may be advantageous in reducing the effects of climate change, it has also created numerous social and financial problems for households in the Netherlands (Mulder et al., 2022). To understand why some individuals engage in energy saving behavior, while others do not, it is vital to explore which factors influence individuals' energy saving behavior. This, together with the integration of the energy crisis, will offer a distinct viewpoint on energy saving behavior. Hence, the research question for this study is as follows: *"What influences individuals' energy-saving behavior in times of an energy crisis in the Netherlands?"*.

1.3 Research Method

This study aims to not only include internal motivations, but also contextual factors contributing to energy-saving behavior. The TPB-ABC integration model will be used in this study, which combines the Theory of Planned Behavior (TPB) by Ajzen (1991) with the Attitude-Behavior-Context (ABC) model by Stern & Oskamp (1987). Although the TPB is frequently used to investigate pro-environmental behavior, it does not take into consideration contextual elements (Conner & Armitage, 1998; Klöckner, 2013; Wang et al., 2021), which are likely to be crucial during an energy crisis. The added ABC model demonstrates that contextual elements are critical in determining whether individuals engage in pro-environmental behavior (Guagnano et al., 1995). Accordingly, the TPB-ABC model has evolved as the interaction between internal motivation and external contexts has become increasingly important in studying consumer behavior (Dong & Hua, 2018; Steg, 2008). Structural Equation Modeling (SEM) will be used in the data analysis to examine the proposed hypothetical model. The target group of this study concerns the general adult population of the Netherlands. A total of 314 individuals participated in the study.

1.4 Scientific and Social Relevance

By taking this approach, the current study aims to understand what influences an individual's energy-saving behavior in times of an energy crisis in the Netherlands. There is arguably a lack of systematic investigation of the decision-making mechanism of sustainable consumption behavior from a multidimensional perspective (Qin & Song, 2022) which is added through this study. A previous study by Qin & Song (2022) used the TPB-ABC model for evaluating Chinese consumer's sustainable behavior, and Dong & Hua (2018) used the TPB-ABC model to determine Chinese consumer's recycling motivation. However, his model has not yet been applied to a specific case of energy conservation nor to a specific time period as the energy crisis which the Netherlands is currently experiencing. The study adds to the current body of literature by using the TPB-ABC model to explore what influences energy saving behavior in times of an energy crisis.

Related to the latter, understanding the factors that contribute and the degree to which they affect energy-saving behavior may also serve as motivation for additional research. For academics and policymakers looking for answers to environmental issues that call for behavioral change, it is critical to have a thorough knowledge of why people engage in energy-saving behavior (Clark et al., 2003). Knowing which factors to consider when analyzing energy-saving behavior has social relevance since it may also assist (governance) practitioners to create their policies and regulations in a more targeted manner.

The Netherlands is chosen as a case study since there is presently no research on the influencing factors on energy-saving in times of an energy crisis, although the energy crisis has a significant impact on Dutch residents according to I&O Research (2022).

1.4 Reader

The study continues by presenting a literature review, including the definition of energy saving behavior and relevant findings of related previous studies. The third chapter presents the theoretical framework based on the TPB-ABC model and proposes the hypotheses. The fourth chapter consists of the methodology including a step-by-step plan for the Structural Equation Modeling (SEM) used to analyze the data. The fifth chapter includes the results of this study. Accordingly, the sixth and seventh chapters present the discussion and conclusion. Lastly, limitations of the present study will be discussed and recommendations will be provided for future research.

2. Literature Review

2.1 Energy-Saving Behavior

Energy-saving behavior (also called: energy conservation) is described by Trotta (2018) as the everyday and regular actions with the aim to reduce energy consumption. Liu et al. (2021) and Steg (2008) add that energy-saving behavior is classified as pro-environmental behavior, which they more specifically described as altruistic, contributive behavior toward environmental conservation. According to Trotta (2018), there are multiple forms of energy saving behavior. First, individuals can save energy by adopting more energy-efficient technologies or increasing the energy-efficiency of appliances (Trotta, 2018). According to Steg et al. (2015), switching to energy-efficient equipment can significantly save energy in the domestic setting. Second, individuals can minimize their energy use through two forms of energy-saving behavior. The first type of behavior is known as curtailment behavior, which is considered a 'low cost' behavior such as taking shorter showers and turning off lights when they are not in use (Steg et al., 2015). The second form of energy saving behavior is considered more 'high cost' and entails the avoidance of actions such as taking hot water showers and machine drying clothing (Steg et al., 2015).

2.2 Factors Influencing Energy-Saving Behavior

In general, Western countries such as the Netherlands have a high degree of concern regarding environmental and energy-related issues (Poortinga et al., 2002). According to I&O Research (2022), about 72% of the Dutch population is 'very concerned or somewhat concerned' about the climate, which is an increase since February 2020 (65%). Also, the urgency of climate change seems to be growing compared to 2020. More people are 'very concerned' about the climate (25% versus 18% in 2020), the same number of people are 'somewhat concerned' about the climate (47%). According to Gadenne et al. (2011), environmental attitudes—which are directly connected to environmental ideals, social norms, and community impact—are closely associated with energy-saving activities.

Yet, people often do not act in line with their concerns. (Steg, 2008) noted that total household energy use was still rising. Steg (2008) argues that people have placed a low priority on saving energy in the past few years due to a lack of knowledge and awareness. However, energy consumption is not merely driven by environmental concerns. Other factors also play a role, such as the amount of effort to alter the behavior, their social status and comfort (Stern, 2000). Accordingly, it is argued that individuals are less inclined to cut their energy use when it involves substantial behavioral costs in terms of money, time, or convenience (Steg, 2008). As a result, Steg (2008) contends that individuals are more inclined to engage in low-cost pro-environmental actions than in high-cost (financial or lifestyle-changing) pro-environmental behaviors. Moreover, Steg (2008) shows that if households only save energy for hedonic or cost reasons, they are more likely to stop the behavior as soon as it is no longer appealing or cost effective. This is significant in light of the current study since it is unclear whether the individuals that saved energy during the energy crisis will continue to do so if the conditions change.

According to other studies, sociodemographics, awareness and attitude, policies, as educational and promotional efforts, as well as moral standards are seen as significant effects on predicting energy-saving behavior (DeWaters & Powers, 2011; Dias et al, 2004; Steg, 2008). Additionally, it appears that personal norms influence people's readiness to change and their energy conservation habits. Reluctance, inability and social impediments are seen as barriers to altering behavior (Vringer et al., 2007).

2.3 Behavioral Change in Times of a Crisis

Abrahamse et al. (2005) show that energy conservation has been a topic of interest for decades. The energy crisis of the 1970s provided incentives for conservation studies, increasing concerns about the probable depletion of fossil resources. Gardner and Stern (2002) then argued that the incentive for research on energy-saving behavior is motivated by environmental concerns. The current energy crisis has a significant impact on Dutch residents, making it interesting and important to investigate energy-saving behavior at this time.

A 'crisis' refers to a scenario with changing conditions which can cause significant anxiety, fear and stress that leads to individuals to change their behavior (Bundy et al., 2017). Behavioral alterations during a crisis can be explained in terms of changing 'mental models'. Mental models are individuals' beliefs about how the world works (Vink et al., 2019) which drives our behavior and understanding of the world influences including the decision-making and coping strategies (Baron, 2006). These mental models are built on life experiences, as well as social, economic and ethical values (Evardsson & Tronvoll, 2021). These shifts in mental models, and hence shifts in behavior, are typically reinforced by institutional arrangements such as regulations and legal enforcement (Evardsson & Tronvoll, 2021). For example, during the COVID-19 crisis, online service platforms created changes in mental models and institutional structures, which improved access to resources and promoted collaboration (Edvardsson & Tronvoll, 2020). The energy crisis, like the COVID-19 situation, has had a significant impact on the population in both developing and developed countries (Farghali et al., 2023). External factors such as rising pricing for products, services, and transportation, as well as decreased purchasing power due to inflation, may therefore lead to changes in individuals' mental models (Farghali et al., 2023).

Behavioral changes, however, vary according to the type of crisis (Guèvremont et al., 2022). For instance, economic crises frequently result in an overall decreased consumption of consumers' expenditures which include limiting their non-essential purchases (Ozdamar et al., 2020). Furthermore, the COVID-19 situation resulted in a complete shift in everyday behavior, with many new forms and patterns of consumption emerging, such as hoarding of goods due to a perceived risk of scarcity (Kirk & Rifklin, 2020) and purchases of cleaning supplies to feel safe (Cambefort, 2020). Therefore, Wood et al. (2005) showed that it is evident that a disruption of a stable context can open doors to new behaviors, especially when the old behaviors are no longer accessible.

Based on the above-mentioned, the energy crisis could also be viewed as an opportunity for change. To transform an existing crisis into an opportunity, the situation must be reframed or viewed through a different lens. Incentives and motives alter during a crisis, which may lead to new cooperative behaviors to tackle the situation at hand. For example, the energy crisis boosts public awareness about energy usage, which may cause households to reconsider their consumption patterns, and allows governments to intervene with new subsidies or programs. In a broader sense, Kentas (2023) argues that the energy crisis might be converted into an opportunity for lowering oil reliance, speeding up sustainable energy initiatives, and increasing efforts to address climate change issues. Reducing households' energy consumption can not only assist to alleviate the present crisis, but it can also promote the transition to net zero and efforts to increase the percentage of renewable sources in the energy mix provided the decrease is sustained over time.

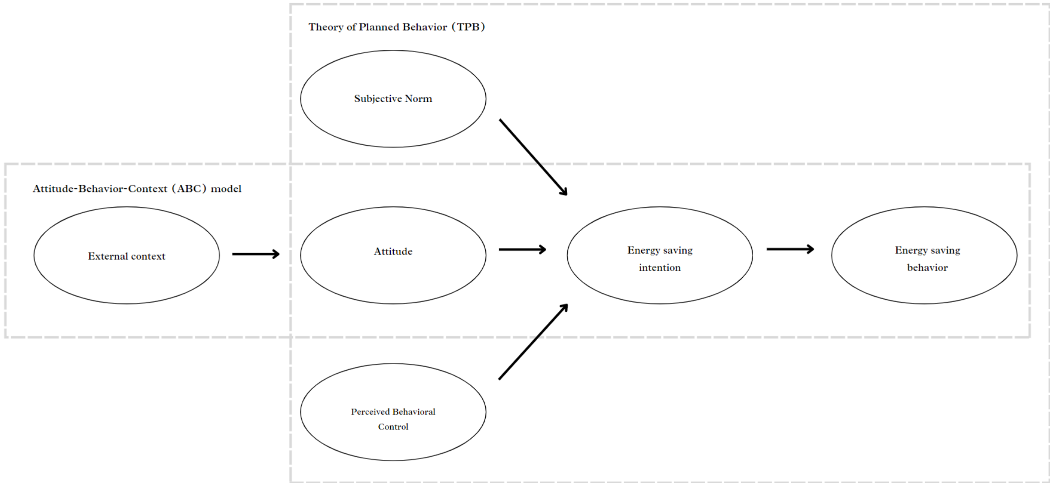
3. Theoretical Background and Research Hypotheses

3.1 TPB-ABC Integration Model

The TPB-ABC integration model consists of a combination of the Theory of Planned Behavior (TPB) and the Attitude-Behavior-Context (ABC) model. The TPB is a well-known psychological Theory of Planned Behavior (TPB) by Ajzen (1991). TPB is typically used to determine the impact of different factors influencing (pro-environmental) behaviors (Ajzen, 1991). The theory contends that an individual's behavior is the result of three internal motivational factors which are: 1) Attitude, 2) Subjective norm, and 3) Perceived behavioral control (Ajzen, 1991). To examine these contextual factors, the Attitude-Behavior-Context (ABC) theory by Guagnano et al. (1995) is used to explore the influence of external contexts on energy saving behavior. The ABC theory by Stern & Oskamp (1987) proposes that pro-environmental behavior results from a series of causal relationships between external and internal factors and is therefore a valuable addition to TPB. Guagnano et al. (1995) explained the ABC model Behavior (B) being the result of the joint action of Attitude (A) variables and contextual (C) factors.

TPB-ABC has evolved as more academics attribute consumer behavior to the interaction of internal motives and external factors. For example, a recent study by Qin & Song (2022) explored the determinants, influences, and decision-making processes of Chinese consumers' sustainable consumption behavior using the TPB-ABC integration model. Its validity has been confirmed by several studies including Dong & Hua (2018); Qin & Song (2022), and Zhang et al. (2021). This model has not yet been applied to the specific issue of energy conservation, but it appears to be a promising method as Dong & Hua (2018) demonstrated that internal motivations and external settings are important factors in predicting pro-environmental behavior.

Figure 1. Theoretical Framework TPB-ABC integration model adapted from Qin & Song (2022).



3.2 Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (TPB) proposed by Ajzen et al. (1991) is a widely utilized psychological model which claims that an individual's behavior is predicted by their intention to perform that behavior. TPB is an extension of the Theory of Reasoned Action by adding the variable 'perceived behavioral control', which enhances the understanding of human behavior better in settings where the person feels they have little or no control over his behavior (Ajzen, 1991). TPB has explanatory and predictive capacity when it comes to researching the mental decision-making process of particular goal-oriented behaviors. Accordingly, it has been used in numerous research to explain for example pro-environmental behavior (Du & Pan, 2021; Gao et al., 2017; Suntornsan et al., 2022). TPB is based on the premise that individuals make rational decisions to engage in specific activities based on available information and knowledge (Suntornsan et al., 2022). However, there is substantial debate over the premise of rationality since humans occasionally respond emotionally rather than rationally. Unconscious impacts on behavior (Sheeran et al., 2013) and the involvement of emotions (Conner et al., 2013) are also thought to play a significant part in decision-making. This study employs the TPB to investigate individuals' internal motivation to engage in energy-saving behavior.

3.2.1 Attitude (AT)

The TPB's initial variable which influences a person's behavioral intention is 'attitude'. Attitude, as an important psychological characteristic, represents one's positive or negative assessment of certain behaviors by evaluating its cost and benefits (Ajzen, 1991). Hence, the more positive an individual's attitude toward saving energy, the more likely they intend to engage in that behavior. Multiple studies, including Gao et al. (2017), Webb et al. (2013) and Zhang et al. (2013), have demonstrated the importance of attitude in predicting energy saving behavior. When applied to this case, this indicates that if individuals believe energy-saving to be essential to them, they are more likely to have a favorable attitude toward it and, as a result, are more likely to perform that kind of behavior. As a result, the following is hypothesized:

Hypothesis 1. *Positive attitude towards energy saving positively impacts an individuals' energy saving behavior.*

3.2.2 Subjective Norm (SN)

The second variable in the TPB which affects an individual's behavioral intention consists of the 'subjective norm'. Subjective norms indicate that individuals conform to the expectations or perspectives of others who are important to them (Gao et al., 2017). Similarly, Liu et al. (2021) showed that one's aim to save energy requires the approval of individuals who are important to them. Individuals are more inclined to undertake a behavior if they perceive a higher subjective norm associated with that behavior (Gao et al., 2017). In the context of energy saving behavior, this implies that if an individual learns that other people, that are considered important to them, believe they should save energy in their house, he or she will experience pressure and be more inclined to save energy. As a result, the following is hypothesized:

Hypothesis 2. *Positive subjective norms positively impact an individuals' energy saving behavior.*

3.2.3 Perceived Behavioral Control (PBC)

The third important variable to affect an individual's behavioral intention in the TPB is perceived behavioral control. This variable contends that there might be certain elements (such as time, opportunity, knowledge, resources, ability) that are outside of the control of an individual which might impact one's intention to perform a certain behavior (Gao et al., 2017). Ajzen (1991) argues that perceived behavioral control relates to an individual's assessment of the ease or difficulty of engaging in a given behavior. Accordingly, if an individual perceives a significant amount of control over their situation or their behavior, they are more intended to perform energy saving behavior (Qalati et al., 2022). Gao et al. (2017) also confirms that a higher degree of control over an individual results in a stronger intention to perform a certain behavior. As a result, the following is hypothesized:

Hypothesis 3. *High perceived behavioral control positively impacts an individuals' energy saving behavior.*

3.2.4 Shortcoming TPB

Despite its proven usefulness for studying an individual's energy saving behavior, it does have a shortcoming. According to the TPB, three major elements impact behavior intention: attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991). These are internal to the individual and focus on their beliefs, values, and perceived control over their conduct (Ajzen, 1991). So, the TPB stresses the importance of internal motives in influencing behavioral intentions. The TPB, on the other hand, does not expressly evaluate the impact of external or contextual variables on behavior (Conner & Armitage, 1998; Klöckner, 2013; Wang et al., 2021). Situational restrictions, societal conventions, economic incentives, and governmental initiatives are examples of external variables (Olli et al., 2001). These factors can have a considerable influence on an individual's actual behavior (Olli et al., 2011). To deal with this, the study proposes an additional component to the TPB model, known as the Attitude-Behavior-Context (ABC) theory. Besides that link between attitude and behavior, the ABC theory also includes contextual factors such as monetary incentives, policies and regulations (Olli et al., 2011). A unique perspective on energy-saving behavior is offered by this addition.

3.3 Attitude-Behavior-Context Theory (ABC)

The Attitude-Behavior-Context model (ABC-model) by Stern and Oskamp (1987) and Guagnano et al. (1995) connects interaction of individual attitudes with external conditions. The ABC-model was added to the TPB as Wand et al. (2021) argue that the latter ignores the external context that is crucial in exploring the determinants of certain behavior. Limiting the model to internal motivation leads to an inadequate understanding of the factors of pro-environmental behavior (Conner & Armitage, 1998; Wang et al., 2021).

Guagnano et al. (1995) pointed out that the environmental attitude (A) and external contextual factors (C) determine pro-environmental behavior. External contexts can include advertising, government laws, legal and institutional issues, incentives and costs, technical limits, and the availability of infrastructure to support the behavior (Stern, 2000). These external contexts can provide opportunities and generate restrictions for creating personal attitudes and behaviors (Qin & Song, 2022). In this study, external contexts will refer to the present 'positive' and 'negative' contexts in relation to the energy crisis in the Netherlands. This division is used in studies such as Qin & Song (2022) and Casaló et al. (2019). In this study, *positive* contexts are defined as scenarios that are likely to result in an individuals' attitude being favorable towards performing energy-saving behavior. The *negative* contexts refer to scenarios that are likely to result in an individuals' attitude not being favorable towards performing energy saving behavior.

3.3.1 Positive Contexts (PC)

In the ABC model, positive external contexts can positively influence the intention of individuals to perform pro-environmental behavior (Stern, 1999; Qin & Song, 2022). To begin with, Webb et al. (2013) show that energy prices significantly impact the energy consumption of individuals as an increase in energy price often results in a significant reduction of energy consumption (Webb et al., 2013). This is also shown in the study by Maqbool & Haider (2021) which argues that energy costs greatly influence individuals' behavior to conserve energy. Also, inflation plays a role in energy saving behavior. Webb et al. (2013) presents that economic expenditures play a negative role in regulating energy prices, meaning that if other expenditures are high, energy consumption will reduce. Moreover, Oikonomou et al. (2009) argue that financial incentives are insufficient to drive long-term pro-environmental behavior. However, an approach based on advertising and education may increase consumer understanding and awareness of pro-environmental behavior, making it easier for such behavior to be adopted (Oikonomou et al., 2009). Liu et al. (2010) argue that advertising and education of the population have a considerable influence on pro-environmental behavior. In April 2022, the Dutch government launched a national campaign under the name 'zet ook de knop om' ("turn the switch") to encourage individuals by providing practical saving tips to save energy in the short-term (Ministerie van BZK & EZK, 2022). Based on the above mentioned, it is likely that a positive context can have a significant positive impact on energy saving behavior. Accordingly, the following is hypothesized:

Hypothesis 4. *Positive contexts positively impact an individual's attitude towards energy saving behavior.*

3.3.2 Negative Contexts (NC)

Within the ABC model, negative contexts can negatively influence the likelihood of individuals engaging in pro-environmental behavior (Stern, 1999; Qin & Song, 2022). According to Guagnano et al. (1995), negative contextual factors may strongly inhibit pro-environmental behavior. In this scenario, psychological (internal) motivations are seen as relatively unimportant (Guagnano et a., 1995).

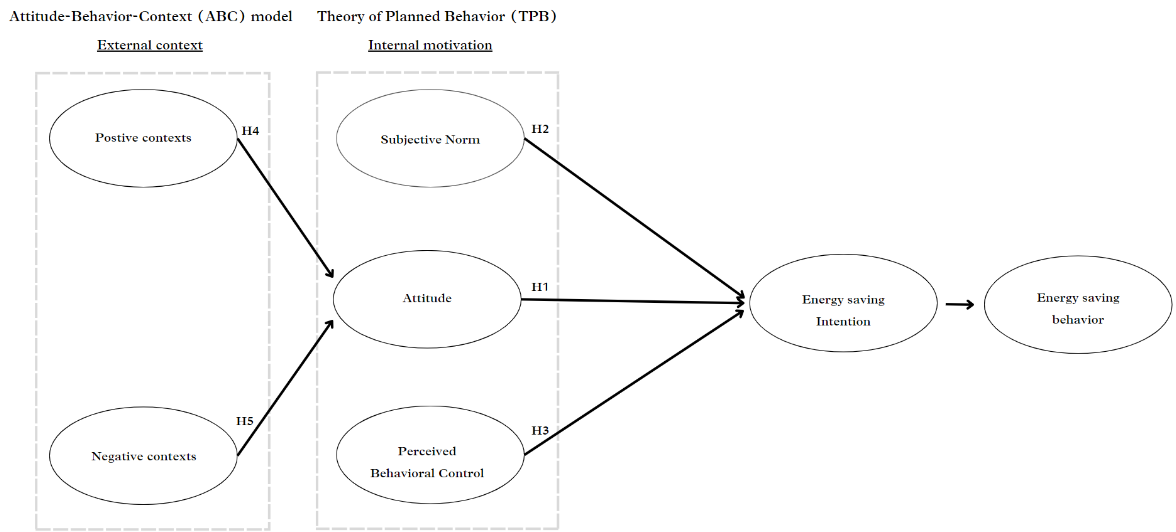
First, Stern (2000) argues that government regulations can impact the intention of individuals to impact energy saving behavior. The Dutch government implemented the price cap which ensures a maximum amount of expenditures on energy and gas with the aim to provide relief for the energy bill (Ministerie van Algemene Zaken, 2023). Notwithstanding the positive effect of financial alleviation, the price cap may have an influence on the intention to engage in energy-saving behavior. For example, Aydin et al. (2017) show that individuals who live in an energy-efficient house, appear to be less concerned with energy conservation. This is known as the so-called 'rebound-effect' which means that increased energy efficiency increases demand for energy services (Aydin et al., 2017). In other words, consumers' behavior tends to adapt to the circumstances. For example, individuals living in a poorly insulated house tend to be more cautious about turning on the heater, as they are afraid of the energy bill (Aydin et al., 2017). Lower income groups are more likely to experience the rebound effect since they are further away from meeting their demands for energy services, particularly thermal comfort (Aydin et al., 2017; Milne & Boardman, 2000). Furthermore, it is argued that individuals with higher incomes may tend to save less energy than their lower income counterparts simply because they can afford to absorb higher energy costs (Aydin et al., 2017; Martinsson et al., 2011).

Hypothesis 5. *Negative contexts negatively impact an individual's attitude towards performing energy saving behavior.*

3.4 Hypothesis Model

Figure 2 introduces the hypothetical model for energy saving behavior during an energy crisis. The model is based on the TPB-ABC model and shows formed hypotheses as proposed in the sections mentioned above.

Figure 2. Hypothesis model of energy saving behavior based on TPB-ABC.



4. Methodology

4.1 Data Collection

This study was conducted using quantitative research. To collect data, a questionnaire was set up to measure the factors influencing individuals' energy saving behavior using self-reports (Gatersleben, 2002). The survey and its measurement items were drawn up on the basis of the literature review. The survey consisted of 21 statements (table 1) that respondents had to answer using a 4-point Likert scale with a range from 1 "completely disagree" to 4 "completely agree". Without a neutral option, this kind of Likert scale enables researchers to offer four extreme possibilities which forces the respondent to form an opinion. However, it should be emphasized that leaving out the midpoint might inflate respondents' actual reactions to the statement or question.

Seven latent variables were used to measure energy saving behavior, which are: Attitude (AT), Perceived Behavioral Control (PBC) Subjective Norm (SN), Positive Context (PC), Negative Context (NC), Intention for Energy Saving Behavior (IESB) and Energy Saving Behavior (ESB). The questionnaire was divided into three main sections that consist of: 1) TPB variables, 2) ABC variables and, 3) the (intention) of energy saving behavior. To do so, a SEM analysis was conducted using AMOS software which is a component of the IBM SPSS Statistics software package.

Before distributing, the questionnaire was pre-tested among peer students to determine the survey's clarity and possible mistakes. This resulted in a few alterations in the formulation of the measurement items. The online questionnaire was prepared using

Qualtrics with a license from the University of Twente. The questionnaire started by asking three demographics (gender, age, level of education) as they are strongly related to pro-environmental behavior (Abrahamse & Steg, 2011). Furthermore, displaying the demographics of the sample population aids in determining if the target group is representative, provides (insights) for duplicating the study, and enables for bias evaluation (Goertzen, 2017).

After that, the questionnaire was divided into three sections based on the theoretical background of the TPB-ABC model (table 1). Positive and negative statements were used to (1) prevent respondents from replying carelessly, and (2) guarantee broader assessment of an attitude or view (Suárez-Álvarez et al., 2018). Completing the survey took a maximum of 3-5 minutes. The survey was conducted using convenience sampling. The distribution channels used included LinkedIn, Facebook and WhatsApp. Moreover, to prevent ethical issues, an introductory statement was provided at the beginning of the survey noting that participation in this study was entirely voluntary. Moreover, the anonymity of the respondents was ensured by only using the three demographic variables as mentioned before. The participants signed an active consent question to ensure voluntary participation and permission to use the data for academic purposes only.

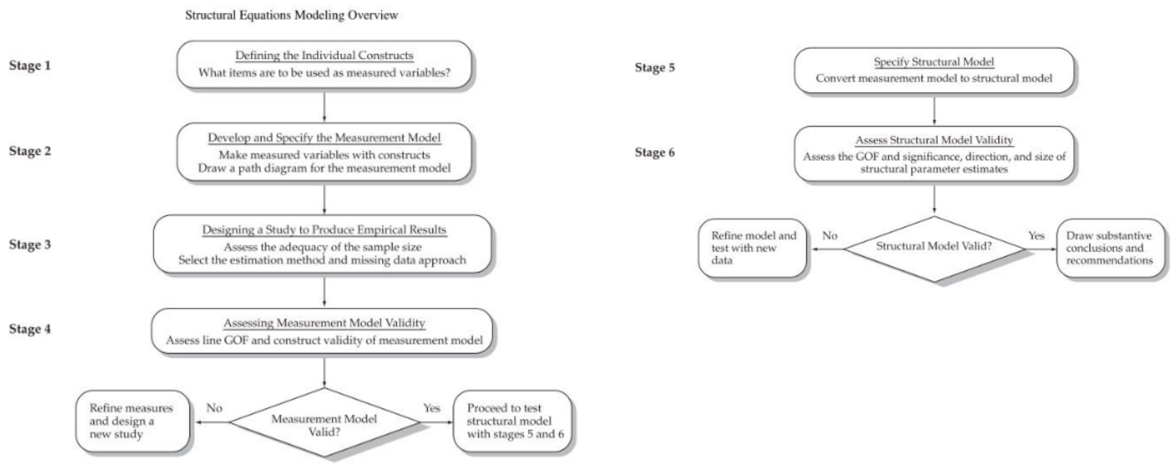
Table 1. Latent variables, measurement items and sources.

Latent Variables	Code	Measurement Items	Source
Attitude	AT1	"Energy saving at home is important during an energy crisis"	Chen & Knight (2014); Du & Pan (2021)
	AT2	"I think that saving energy is worth it because makes a measurable difference to my energy bill"	
	AT3	"I think that saving energy has little effect"	
Subjective Norm	SN1	"People that are important to me think that it is important to save energy"	Gao et al. (2017);; Nie et al (2019)
	SN2	"People around me that are important have not engaged in energy saving behavior"	
	SN3	"People around me that are important have engaged in energy saving behavior"	
Perceived Behavioral Control	PBC1	"I have sufficient time and opportunities for saving energy at home"	Du & Pan (2021); Gao et al. (2017); Nie et al. (2019)
	PBC2	"The high energy costs cause me to lose control over my situation"	
	PBC3	"I do not know how I can reduce my energy costs at home"	
Positive Context	PC1	"Governmental campaigns make me save energy at home"	Maqbool & Haider (2021); Liu et al. (2010); Qin & Song (2022)
	PC2	"The high energy prices make me save energy at home"	
	PC3	"Reduced disposable income (inflation) makes me save energy at home"	
Negative Context	NC1	"The price cap (energie plafond) prevents me from saving energy at home"	Aydin et al. (2017); Martinsson et al. (2011); Qin & Song (2022)
	NC2	"Falling energy prices (will) make me use more energy at home"	
	NC3	"A higher income would make me use more energy"	
Energy Saving Intention	ESI1	"I plan to use less energy at home over the next year"	Gao et al. (2017); Suntornsan et al. (2022);
	ESI2	"I am not willing to engage in energy-saving behavior at home"	
	ESI3	"I plan to install (more) energy saving devices in my home"	
Energy Saving Behavior	ESB1	"I engage in energy saving behavior at home"	Du & Pan (2021); Suntornsan et al. (2022)
	ESB2	"I am conscious of my energy consumption at home"	
	ESB3	"I reduced my energy consumption at home in the past year"	

4.2 Data Analysis

Structural Equation Modeling (SEM) was used in the data analysis to examine the proposed hypothetical model (figure 2). SEM is often used to evaluate latent variables on measurement models and test hypotheses between latent variables on structural models (Hair et al., 2011). It is argued to be particularly useful in energy consumption studies, where there are several dependent variables (Kline, 2016). Moreover, SEM makes it possible to incorporate observed variables (indicators) and unobserved (latent) variables in a single model. SEM has been used in several studies regarding measurement of pro-environmental behavior in relation to certain variables such as Du & Pan, (2021); Ertz et al. (2016); Gao et al. (2017); Qin & Song (2022) and Suntornsan et al. (2022) and has proven to an effective method of data collection in related cases. The following figure (3) by Hair et al. (2014) shows the stages of SEM.

Figure 3. Structural Equation Modeling stages by Hair et al. (2014).



4.2.1 Procedure

The first stage included defining the 'individual constructs' based on a theoretical background (figure 1). Based on that, a hypothesis model (figure 2) was defined using seven latent variables: Attitude (AT), Perceived Behavioral Control (PBC) Subjective Norm (SN), Positive Context (PC), Negative Context (NC), Intention for Energy Saving Behavior (IESB) and Energy Saving Behavior (ESB). Also, the measurement items were defined based on existing literature (table 1).

The second stage included developing and specifying the measurement model. A measurement model is a SEM model that consists of indicators (also called measurement items) for each construct which allows an assessment for construct validity (Hair et al., 2014). The construct validity measures how well the measured variables match the theoretical concept (in this example, TPB-ABC) they are intended to assess (Hair et al., 2014). To do so, a path diagram was drawn in SPSS AMOS.

The third stage included producing empirical results (descriptive statistics) that provided an overview of the sample characteristic. Also, the data was checked for multivariate outliers as suggested by Hair et al. (2014) using "Mahalanobis distances", which is a feature in the SPSS software. Mahalanobis distances compare each observation's location to the center of all observations for a collection of variables (Hair et al., 2014; Kline, 2016). This is essential as significant multivariate outliers in the data might distort the model (Hair et al., 2014). That is because multivariate outliers have the ability to have a disproportionate effect on the estimated parameters, possibly resulting in a weak overall model fit (Hair et al., 2014) or jeopardize fit indices (Kline, 2016). These are calculated for the variables to be entered on the multiple regression analysis and their results are divided by the number of variables. When sample sizes are large (100+), coefficients above 3.5 or 4.0 can be considered outliers (Hair et al., 2014). Results showed that no multivariate outliers were present in the data.

A total of 314 individuals participated in the study. The target group of this study concerned the general population of the Netherlands. Participation in this study required being over the age of 18 and currently living in the Netherlands. The data's missing cases were analyzed and 12 data cells were empty on 11 different variables. The maximum number of missing cases on a single variable was 2 which were replaced by the variable's means as this amount of missing data is negligible. After the data cleaning, 233 responses were used in the data analyses. After the research was completed, all data was deleted.

The fourth stage included testing the measurement model using the Maximum Likelihood Estimation (MLE) approach. MLE is a feature of the SPSS AMOS program used in SEM as it is the default program to calculate estimates (Hair et al., 2014; Kline, 2016). Early attempts of SEM were performed using Ordinary Least Square (OLS) regression, however this was replaced by MLE as this technique appears to be less biased and more efficient when normality of the model is met (Hair et al., 2014). This stage also involves assessing the (1) Goodness-Of-Fit (GOF), (2) convergent validity, and (3) construct reliability. The analysis proceeded when the model exhibited good fit. The model was revised when this was not the case. The following table shows (2) the definitions and rules of thumb for assessing the measurement model based on Hair et al. (2014).

Table 2. Fit indexes and rules of thumb by Desivilya et al. (2015) based on Hair et al. (2014).

Fit index	**Definition**	**Rules of thumb**
Normed chi-square (χ^2/df) (CMIN)	The likelihood ratio. Indicates if the sample data and hypothetical model are an acceptable fit in the analysis.	The division between the chi-square value and the model's degrees of freedom should be < 4.
Root mean square error of approximation (RMSEA)	Measures the difference between the observed covariance matrix per degree of freedom and the predicted covariance matrix.	RMSEA < 0.08
Comparative fit index (CFI)	Analyzes the model fit by examining the discrepancy between the data and the hypothesized model.	CFI > 0.90
Normed fit index (NFI)	Consists of values scaling between independence model (bad fit) and saturated model (good fit).	NFI > 0.90

Indicator of convergent validity	Definition	Rules of thumb
Factor loadings (λ)	Correlation between the original variables and the factors, and the key to understanding the nature of a particular factor. Squared factor loadings indicate what percentage of the variance in an original variable is explained by a factor.	In the case of high convergent validity, high one-factor loadings would indicate that they converge on a common point, the latent construct. At a minimum, all factor loadings must be statistically significant. Because a significant load can still have quite weak strength, a good rule of thumb is that standardized loading estimates should be 0.5 or higher and ideally 0.7 or higher.
Average Variance Extracted (AVE)	A summary measure of convergence among a set of items representing a latent construct. It is the average percentage of variation explained (variance extracted) among the items of a construct.	An AVE of 0.5 or higher is a good indicator for suggesting adequate convergence. An AVE of less than 0.5 indicates that, on average, more error remains in the items than variance explained by the latent factor structure imposed on the measure.

Indicator of internal consistency	Definition	Rules of thumb
Construct Reliability (CR)	Measure of reliability and internal consistency of the measured variables representing a latent construct. Must be established before construct validity can be assessed. It is computed from the squared sum of factor loadings for each construct and the sum of the error variance terms for a construct.	0.7 or higher suggests good reliability. Reliability between 0.6 and 0.7 may be acceptable, provided that other indicators of a model's construct validity are good.
Cronbach's Alpha	Cronbach's Alpha is a measure of reliability that ranges from 0 to 1.	0.6 - 0.7 is the minimum acceptable level.

The fifth stage included specifying the structural model. Only if the measurement model is considered 'valid', can it be converted into a structural model. A structural model can be defined as a set of dependent relationships connecting the hypothesized models' constructs (Hair et al., 2014). The second model (figure 4) did not show a perfect fit, so trade-offs were made based on the estimates' regression weights (< .4 = delete), the AVE (< .5 = delete) and CR (< .7 = delete) (Appendix 1). Estimates of regression weights refer to the coefficients that quantify the relationship between variables in a regression model (Hair et al., 2014). Nevertheless, despite the presence of a rather poor regression weight, several items were maintained based on the trade-off of having a sufficient CR score (Appendix 1). Finally, Modification Indices (MI) were utilized to determine which relationships the SEM program had identified as significant to the model.

The sixth and last stage included testing whether the structural model can be considered valid (figure 5). Conclusions and recommendations were drawn based on the model coefficients which showed the parameters for each construct.

4.3 Sample Characteristics

Table 3 shows the frequency of responses for each categorical variable being studied. The ratio of male to female respondents in the sample was approximately 1:3 (61:168). This is most likely due to the survey being circulated within the researchers' personal network, which includes many female child care professionals. Moreover, one responder identified as non-binary/third gender, and four others preferred not to disclose this information. In terms of age, the distribution is quite equal, with all age groups falling between the 12% and 18.9% range (with the exception of those 66 years and above). The majority of the sample (50.4%) indicated having higher professional education (HBO); the second-largest group (27.6%) indicated having secondary vocational education (MBO); the third-largest group (12.9%) indicated having university education (WO).

Table 3. Sample characteristics.

		Count	Column N %
Gender	Female	168	72.1%
	Male	61	26.2%
	Non-binary/third gender	1	0.4%
	Prefer not to say	3	1.3%
Age	18-25 year	36	15.5%
	26-33 year	44	18.9%
	34-41 year	28	12.0%
	42-49 year	34	14.6%
	50-57 year	41	17.6%
	58-65 year	38	16.3%
	66 year or older	12	5.2%
Education	Higher professional education (HBO)	117	50.4%
	No education completed	1	0.4%
	Pre-university education (VWO)	1	0.4%
	Pre-vocational secondary education (VMBO)	5	2.2%
	Secondary vocational education (MBO)	64	27.6%
	Senior general secondary education (HAVO)	14	6.0%
	University education (WO)	30	12.9%

5. Results

The findings of this study are divided into three sections. The first being descriptive statistics which provides a summary of the data. Second, the test of the measurement model will be presented which specifies the number of factors and their indicators. Third, the test of the structural model which shows how the factors are related to each other in terms of indirect or direct effects, or no relationship.

5.1 Descriptive Statistics

The table that follows provides descriptive data for each variable being examined. Table 4 shows the minimum and maximum values of each constructed scale. Also, the mean, standard deviation, skewness and kurtosis are included. Skewness and kurtosis are used to examine the normality of variables (variables that follow a normal distribution). “Skewness” measures the symmetry of a distribution and it is compared to the normal distribution (Hair et al., 2014). “Kurtosis” measures the ‘peakedness’ of the distribution and is also compared to the normal distribution (Hair et al, 2014). Both values should remain between -1 and 1 to indicate normality (Hair et al., 2014). In this study, skewness was within ±2 range in most of the cases and so was kurtosis, suggesting normality. Though the focus is on the relative fit of the model and the sample size is large, which makes it less significant (Hair et al., 2014), a small deviation from normality was found for AT2 and ESB3.

The total sample size was 233 (N = 233). Items coded with the suffix ‘_INV’ indicate items that were ‘reverse-coded’. Reverse coding means, for example, rephrasing a “positive” item in a “negative” manner. Reversing survey items can aid in (1) preventing respondents from replying carelessly, and (2) guaranteeing broader assessment of an attitude or view (Suárez-Álvarez et al., 2018). According to Hair et al. (2014), reverse-coding, also known as reverse-scoring, is the act of reversing the data values for variables in order to reverse their correlations with other variables. It serves to prevent variables with positive and negative loadings from canceling one another out (Hair et al., 2014). For instance, variable AT3 "I think that saving energy has little effect”; Respondents' "positive" responses—in this example, "completely agree"—would constitute a "negative" reaction to energy-saving behavior. Another variable of AT, such as AT1 represented as “Energy saving at home is important during an energy crisis” does provide a “positive” reaction if responded by “completely agree”. Thus, if AT3 was not reverse-coded, AT3 and AT1 would cancel each other out.

Table 4. Descriptive statistics of variables.

Code	Minimum	Maximum	Mean	Standard Deviation	Skewness	Kurtosis
AT1	1	4	3.392	.599	-.546	.083
AT2	1	4	3.524	.695	-1.677	3.200
AT3_INV	1	4	3.416	.745	-1.037	.245
SN1	1	4	3.077	.659	-.631	1.269
SN2_INV	1	4	3.039	.767	-.354	-.471
SN3	1	4	3.176	.629	-.467	.819
PBC1	1	4	2.952	.744	-.302	-.244
PBC2_INV	1	4	2.784	.922	-.090	-1.016
PBC3_INV	1	4	3.279	.806	-1.047	.707

PC1	1	4	2.189	.918	.020	-1.155
PC2	1	4	3.180	.789	-.969	.916
PC3	1	4	2.267	.936	.108	-.958
NC1	1	4	1.781	.820	.804	-.032
NC2	1	4	1.707	.825	.872	-.189
NC3	1	4	1.573	.773	1.191	.645
ESB1	1	4	3.343	.703	-1.045	1.395
ESB2	1	4	3.500	.630	-1.201	1.785
ESB3	1	4	3.463	.792	-1.612	2.253
ESI1	1	4	3.352	.758	-1.167	1.256
ESI2_INV	1	4	3.336	.955	-1.258	.395
ESI3	1	4	3.004	.763	-.419	-.169

5.2 Test of the Measurement Model (Confirmatory Factor Analysis)

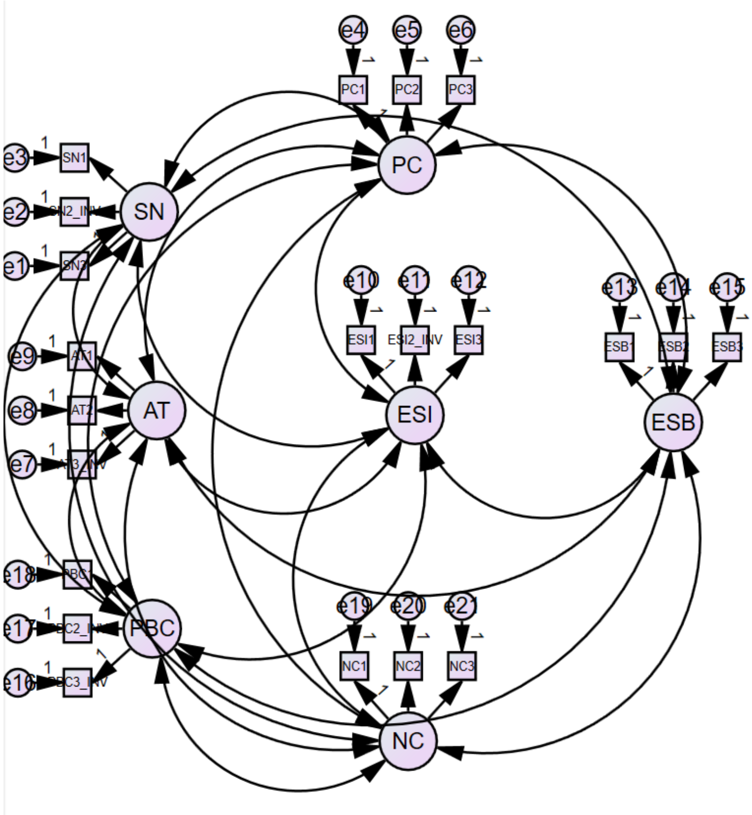
The main objective of testing the measurement model is to test construct validity. "Construct validity", as previously determined, refers to testing the degree to which the model's variables accurately reflect the theoretical framework that they are intended to assess (Kline, 2016). In other words, it measures how well the indicators evaluate the concept (Hair et al., 2014). After testing construct validity, the study employed Confirmatory Factor Analysis (CFA), which is a suitable technique for demonstrating the construct validity of theory-based instruments (Li, 2016). CFA is often employed when there is a precise pattern of variables that is predicted by theory (DeVellis, 2012; Hair et al., 2014), in this case TPB and ABC (figure 2). Construct validity assessments in combination with CFA findings can help researchers better grasp the quality of their measures (table 5) (Hair et al., 2014). The model was set up in AMOS using 'covariances' (double-sided arrows) which represent a relationship between variables X and Y (Kline, 2016). More covariances were indicated in the model than theoretical underpinned as SEM has the benefit of suggesting additional testing paths to improve the model fit (Hair et al., 2014). If the covariances are not included in the model, then these extra pathways cannot be provided.

The findings of the CFA were estimated using the Maximum Likelihood Estimation (MLE) method (Li, 2016). As previously indicated, MLE is the current default setting to calculate estimates in SEM. Estimates are numerical values computed in SEM to ascertain unknown parameter values between observed and unobserved variables. They aid to evaluate model fit, test hypotheses, and enable comparison of various models (Kline, 2016). The MLE initially failed to function in AMOS because a row of missing values was still inserted at the end of the data file, which prevented the MLE from analyzing the data set (Kline, 2016). The MLE worked effectively once the empty row was eliminated.

There are three further stages to assess the construct validity following the creation of the path diagram in SPSS AMOS and the analysis which was indicated before. That includes, the assessment of the 1) model fit, 2) convergent validity, and if necessary, 3) respecification of the model. Table 4 lists the fit indices that were employed along with their general rules of thumb. Convergent validity can be defined as "the extent to which indicators of a specific construct converge or share a high proportion of variance in common" (Hair et al. 2014, p. 601). Then, the construct's reliability was tested. This was done using the Composite Reliability (CR) (based on factor loadings) and Cronbach's Alpha (based on correlations)(table 2). CR is also referred to as 'Construct Reliability' and measures the reliability and the internal consistency of the variables measured in the model (Hair et al., 2014). A higher number of CR (at least above .5) means appropriate convergent validity for the variables in the model. The Crohnbach's Alpha (α) reliability of the variables is measured by the Crohnbach's Alpha, which has a range of 0 to 1 and a lower limit of 0.6. A higher value indicates higher reliability.

A summary of the indicators used to measure constructs' validity and reliability are presented in table 5 and 6. Table 7 and 8 provide an overview of the indirect and direct effects of the variables as an additional explanation of the outcomes. The following path diagram was used to test the measurement model is shown below (figure 4).

Figure 4. Model 1 - Path diagram to test measurement model.



The measurement model (figure 4 - model 1) did not reach an adequate Goodness of Fit due to 'negative definite covariance matrix'. Meaning that, the variables were inversely related to each other, demonstrating the need to revise the model. The factor loadings (λ) were estimated and several factor loadings were below 0.400, indicating lack of convergent validity on several constructs. Simply put, some variables were weakly related to the latent construct, and therefore needed revision. For instance for the variables, NC1 (λ = 0.339), PC1 (λ = 0.303), PC3 (λ = 0.280), ESI2_INV (λ = 0.325), SN2_INV (λ = 0.299) and PBC2_INV (λ = 0.399), low factor loadings were present (table 5). After eliminating these components, the model was rerun in AMOS, and the fit was acceptable. Unfortunately, the PC construct in this model had to be reduced to a single-item construct as two of its three items showed poor loadings in the measurement model. Furthermore, two constructs (ESI and PBC) still showed unacceptable indices of reliability (CR required to be over 0.7; or above 0.6 for an acceptable fit), but PBC (CR = 0.354) and ESI (CR = 0.470) were significantly lower. Both variables also did have acceptable validity (AVE < 0.500). Since they were already composed of only two items (see example above "PBC2" and "ESI2"), there was no option but to use single-item constructs to represent PBC and ESI (intention). After running the model again, the measurement model indicated a good-fit (χ^2/df = 1.731, RMSEA = 0.056, CFI = 0.957, NFI = 0.906, IFI = 0.958). The reliability of the model was considered acceptable (CR > 0.600). All Cronbach's Alpha (α) above 0.700, Average Variance Extracted (AVE) above 0.500, and Composite Reliabilities (CR) above 0.700 (table 5). All factor loadings (λ) were above 0.500 (except for one - see table 5), also suggesting appropriate convergent validity (table 5). Trade-offs were made based on the estimates' regression weights (< .4 = delete), the AVE (< .5 = delete) and CR (< .7 = delete). Nevertheless, despite the presence of a rather poor regression weight, several items were maintained based on the trade-off of having a sufficient CR score (Appendix 1).

Table 5. Indicators of internal consistency.

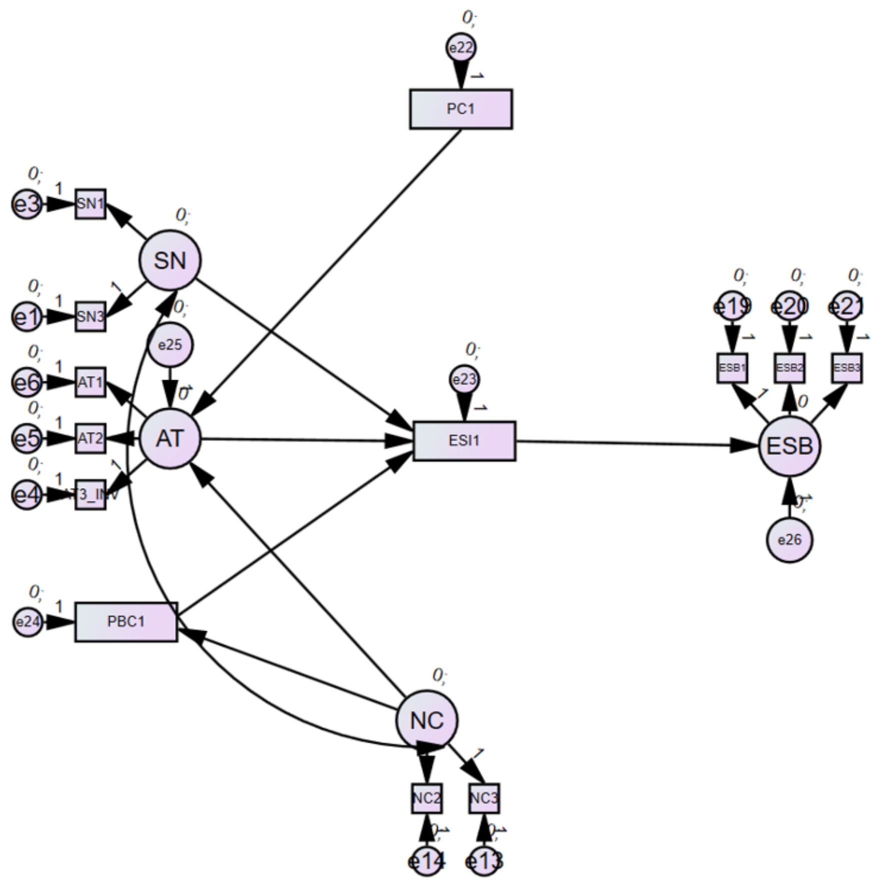
Construct	Item	λ	AVE	CR	α
Subjective Norm	SN1	0.771	0.645	0.784	0.783
	SN3	0.834			
Attitude	AT1	0.585	0.411*	0.676	0.667*
	AT2	0.702			
	AT3_INV	0.631			
Negative Context	NC2	0.718	0.526	0.690	0.690*
	NC3	0.733			
Energy Saving Behavior	ESB1	0.706	0.392*	0.653	0.639
	ESB2	0.665			
	ESB3	0.484*			

*Trade-offs were made for these variables (Appendix 1).

5.3 Test of the structural model (Confirmatory Factor Analysis)

After testing the measurement model, the next step is testing the structural model which is necessary for testing the hypotheses (Hair et al., 2014; Kline, 2016). The model (figure 5 - model 2) did not reach an appropriate fit (χ^2/df = 3.187, RMSEA = 0.097, CFI = 0.802, NFI = 0.742, IFI = 0.807). Consequently, Modification Indices (MI) were used to calculate how much the chi-square would be decreased if one of the model's parameter restrictions were removed. Differently put, MI suggests additional paths to the model that may help to explain the model in a different way (Kline, 2016). The expected increase in overall fit if a specific path was added to the model is better, and this is correlated with the value of the MI (Kline, 2016). In the study, an examination of MI suggested two paths that could modify the Chi-Square by more than 10.000. SN predicting AT (MI = 17.618) and AT predicting PBC (MI = 13.441). These two paths were added to the model but CFI was still below 0.900, suggesting poor fit (χ^2/df = 2.283, RMSEA = 0.074, CFI = 0.892, NFI = 0.827, IFI = 0.895). The next largest modification index was inserting a path from AT directly to ESB (MI = 9.510), and thereby passing ESI. After doing so, the resulting model showed a good fit (χ^2/df = 1.861, RMSEA = 0.061, CFI = 0.929, NFI = 0.862, IFI = 0.931).

Figure 5. Model 2 - Path diagram to structural model



The final model (figure 6 - model 3) represents the model with standardized beta coefficients. Standardized beta coefficients (mean = 0, standard deviation = 1) explain the relationships between the constructs and enable a comparison of the effects of different variables (table 6). It can be observed that 42.4% of the variance of ESB was explained by the model (R^2 = 0.424). Meaning that, in this case the variables ESI(1) and AT predict ESB for 42.4%. However, AT has a far greater impact on ESB than ESI(1), as can be shown, for instance, in the probability score (p) (table 6). The variable ESI(1) has a p-value of .267, which indicates that the likelihood that it would accurately predict ESB is not as significant as AT's p-value < 0.001, which indicates a (very) high probability. Moreover, while AT does have a significant impact on ESI ($p < 0.001$), SN and PBC appear to have no effect on ESI (both variables $p > 0.05$).

Furthermore, ESI has no impact on ESB ($p > 0.05$). However, AT appears to have a direct effect on ESB ($\beta = 0.578$, $p < 0.001$). Also, PBC and SN both have positive effects on AT ($p < 0.05$). An examination of indirect effects (table 7) showed that SN has an indirect effect on ESB ($z = 0.278$), while PBC has no indirect effect on ESB ($z = -0.010$), and AT also has a slight indirect effect on ESB ($z = 0.076$). In these situations, the term "indirect effect" refers to the impact of an independent variable on a dependent variable through the mediation of one or more other model variables (Kline, 2016). However, even if there is no mediator present, indirect effects might still exist in SEM. Indirect effects are relevant as they may (1) provide (additional) knowledge about relationships, (2) contribute to the creation of theories, and (3) assist in comprehending the underlying processes connecting variables (Hair et al., 2014).

Furthermore, the model suggests that ESB is highly explained by AT, directly. It also suggests that SN, PC and NC are direct predictors of AT and indirect predictors of ESB. Furthermore, the table shows that NC has no effect on PBC ($p > 0.05$), but has a negative effect on AT ($\beta = -0.256$, $p < 0.05$).

Figure 6. Model 3 - Final structural model

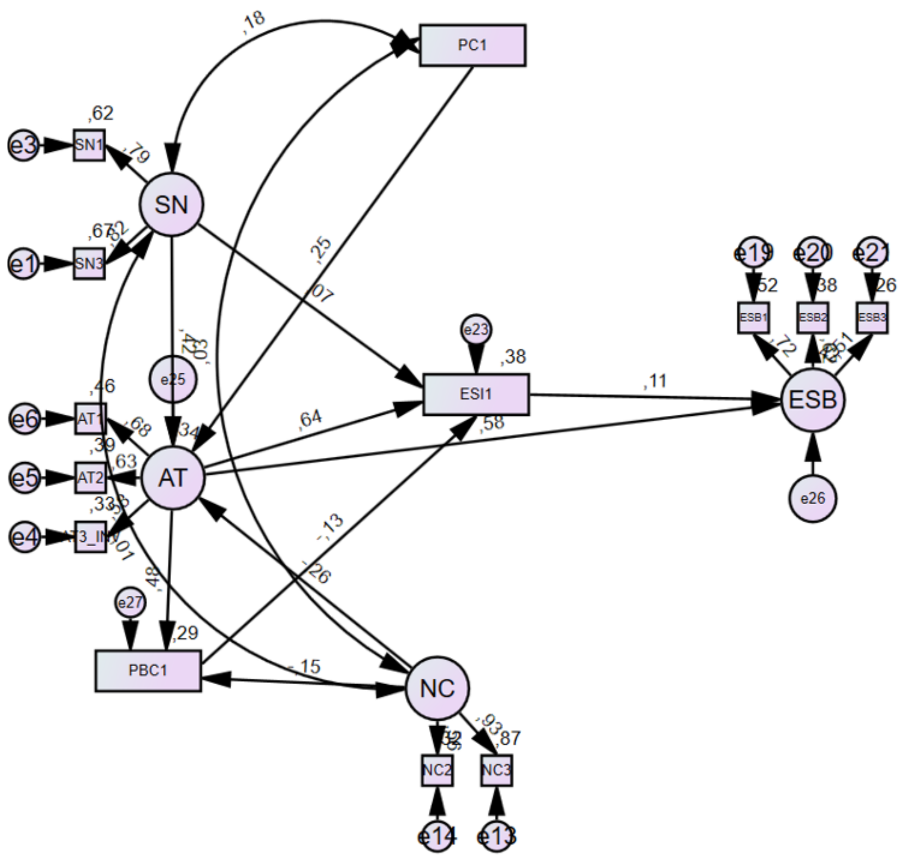


Table 6. Model coefficients based on results.

Constructs			B unstandardized coefficient	β Beta (slope)	S.E. Standardized error	C.R. Capability Ratio	R^2 Coefficient of determination	p Probability
NC	→	**AT**	-.152	-.256	.062	-2.450		.014
PC1	→	**AT**	.115	.246	.034	3.378	.341	***
SN	→	**AT**	.351	.422	.081	4.331		***
NC	→	**PBC1**	-.155	-.151	.081	-1.910	.292	.056
AT	→	**PBC1**	.837	.482	.153	5.478		***
SN	→	**ESI1**	.101	.069	.119	.847		.397
AT	→	**ESI1**	1.125	.637	.219	5.139	.379	***
PBC1	→	**ESI1**	-.129	-.127	.076	-1.697		.090
ESI1	→	**ESB**	.075	.112	.068	1.109	.424	.267
AT	→	**ESB**	.685	.578	.158	4.326		***

***: $p < 0.001$ suggesting high probability

Table 7. Indirect effects (z-score)*.

	SN	**NC**	**PC1**	**AT**	**PBC1**	**ESI1**
PBC1	,309	-,134	,099	,000	,000	,000
ESI1	,365	-,136	,117	-,118	,000	,000
ESB	,278	-,116	,087	,076	-,010	,000
ESB3	,223	-,093	,070	,613	-,008	,060
ESB1	,278	-,116	,087	,761	-,010	,074
AT1	,338	-,147	,108	,000	,000	,000
AT2	,362	-,157	,116	,000	,000	,000
AT3	,356	-,155	,114	,000	,000	,000

* The table does not include variables that resulted in values of 0.000 (no relationship).

Table 8. Direct effects (z-score)*.

	SN	**NC**	**PC1**	**AT**	**PBC1**	**ESI1**
PBC1	,356	-,155	,114	,000	,000	,000
ESI1	,095	,000	,000	1,144	-,136	,000
ESB	,000	,000	,000	,685	,000	,074

AT1	,000	,000	,000	,949	,000	,000
AT2	,000	,000	,000	1,017	,000	,000
AT3	,000	,000	,000	1,000	,000	,000
SN1	,997	,000	,000	,000	,000	,000

* The table does not include variables that resulted in values of 0.000 (no relationship).

6. Discussion

This study aimed to understand what influences an individual's energy-saving behavior in times of an energy crisis in the Netherlands. An additional perspective was provided by combining internal motivation (TPB) and external context (ABC) in the study's theoretical framework and applying this to the specific context. The data collection proceeded satisfactorily despite a flaw in the Qualtrics software (see limitations), and N = 233 may be regarded as an appropriate number of participants. In this study, there was a 1:3 male/female gender ratio in the sample population. This was most likely caused by the fact that the researcher's network included more females and that the survey was distributed among child daycare organizations which have many female employees. Although it is unclear from the analysis whether this had an influence on the result, the descriptive statistics are part of the study with the goal of research replicability and to check for biases in the result. Moreover, it is apparent that the majority of the sample (50.4%) indicated having higher professional education (HBO); the second-largest group (27.6%) indicated having secondary vocational education (MBO); the third-largest group (12.9%) indicated having university education (WO). That is noteworthy because, based on CBS data of 2020, 39% of Dutch people have MBO/MAVO diplomas, 25% have HBO diplomas, and 16% have WO diplomas (Ridder et al., 2020). Accordingly, the sample population of this study includes people who have relatively higher levels of education than the Dutch community as a whole. The direct relation of the TPB-ABC variables to educational level were not determined in this study, but serve as additional information as mentioned before. Lastly, table 9 offers a summary of whether the hypothesis statements were supported or not based on the results.

6.1 TPB Component

The Theory of Planned Behavior (TPB) related to sustainable behavior is a well-known and often researched topic (Ajzen, 1991; Du & Pan, 2021; Gao et al., 2017; Suntornsan et al., 2022). However, this study's TPB component of the model produced some unexpected findings. Ajzen (1991) claimed that one's decision to engage in a particular behavior can be predicted by their intention to perform that behavior. This study, however, found no significant relationship between Energy Saving Intention (ESI) and Energy Saving Behavior (ESB). Although a precise explanation cannot be determined, it may be related to incorrect measurement item formulation or even the particular sample population. Also, it is possible that the sample size has economic motivations to cut expenses rather than energy-saving motivations, which would explain why they may not be as driven to conserve energy.

Related to that, it is also possible that the sample group may be less motivated to adopt *further* energy-saving behaviors if they currently already use energy-saving gadgets and/or have implemented energy-saving solutions, such as solar panels. In that situation, there would be no discernible link between the sample's intention to conserve (more) energy and their actual energy-saving behavior. In light of this, it may be necessary to exclude the model's construct ESI to measure energy saving behavior in times of an energy crisis in the Netherlands.

Hypothesis 1 states that a positive attitude (AT) positively impacts an individuals' energy saving behavior (ESB). Multiple studies, including Gao et al. (2017), Webb et al. (2013) and Zhang et al. (2013), have demonstrated the importance of attitude in predicting energy saving behavior. The results of this study show that ESB is directly and highly explained by AT (β = .578). Also, AT appears to be a strong predictor of ESI (β = 637). This outcome is in line with the previously named studies as well as Ajzen's (1991) TPB. Therefore, hypothesis 1 can be considered supported.

Hypothesis 2 states that positive subjective norms (SN) positively impact an individuals' energy saving behavior (ESB) based on TPB. Ajzen (1991) presents that the behavior and thoughts of people surrounding one directly predicts one's behavior. Also Gao et al. (2017) and Liu et al. (2021) showed that subjective norms indicate that individuals conform to the expectations or perspectives of others who are important to them. In contrast to the latter, variable SN did not show an effect on ESI ($p > 0.05$) in this study. Meaning that, within this study, subjective norms are not a predictor of the intention of individual's to perform energy saving behavior in times of an energy crisis in the Netherlands. However, when calculating the indirect effects, SN did appear to have an effect on ESB ($z = 0.279$, $p = 0.001$) and thereby (partly) supporting the hypothesis. This may be explained by SN appearing to be a direct predictor of AT, and AT being a direct effect on ESB. This again demonstrates that the variable ESI may need to be excluded from the model. Furthermore, regarding the SN construct it is observed that the indicator SN2 had to be removed from the model to obtain a good fit. Comparing the indicators used for SN, it becomes evident that SN2 is the only reverse-coded indicator, yet is relatively similar to the other indicators (SN1 and SN3) used for the construct. Indicating that the respondents might not have read the question with full attention or the formulation of the measurement items was ambiguous. In line with Ajzen (1991) Gao et al. (2017); Liu et al. (2021) SN did appear to have an effect on ESB; it did not show a significant relationship with ESI. Therefore, hypothesis 2 can be considered as partly supported.

Hypothesis 3 states that a high perceived behavioral control (PBC) positively impacts an individuals' energy saving behavior (ESB). Ajzen (1991), Gao et al. (2017), and Qalati et al. (2022) argued that forces outside of one's control impact one's intention to perform that behavior. Accordingly, Qualiti et al. (2022) showed that individuals are more intended to perform energy saving behavior if they feel like they are in control. In this study, the construct PBC was reduced to a single item construct leaving only PBC1 as an indicator using the following statement: "I have sufficient time and opportunities for saving energy at home". The results show that PBC does not have an effect on ESI as predicted as the (p >

0.05) which is contradictory to the claims of Ajzen (1991); Gao et al. (2017); Qalati et al. (2022). Additionally, PBC also showed no indirect effect on ESB ($z = -0.014$, $p = 0.161$). Accordingly, this study shows that having sufficient time and opportunities for energy saving behavior do not necessarily encourage individuals' intention to save (more) energy in the future. However, just like SN, PBC does have a positive effect on AT ($p < 0.05$). Based on the above-mentioned, hypothesis 3 can be considered as *not* supported.

Additionally, the Modification Indices (MI) feature of AMOS suggested two additional paths that would improve the overall model-fit, which are interesting to discuss. First, SN served as a predictor for AT (MI = 17.618) in this study. It follows that one's attitude toward a conduct may be predicted by one's belief regarding whether or not other (important) individuals approve or disapprove of the action, which would urge one to engage in or refrain from doing so (Ajzen, 1991). Park (2000) studied the relationship among attitudes and subjective norms and found that, when attitudes are social in origin, there is an overlap between them and subjective norms in Theory of Reasoned Action research. Future study may look at utilizing SN as a predictor for AT in the context of energy-saving behavior, as this has not yet been studied. Second, AT served as a predictor for PBC (MI = 13.441) in this study. Meaning that one' attitude towards certain behavior can help to predict one's perception of the ease or difficulty of performing the behavior of interest (Ajzen, 1991). Although La Barbera and Ajzen (2021) showed that perceived behavioral control may be seen as a moderator of attitude, no studies have been done to examine how attitude affects perceived behavioral control. Future study might want to consider this.

6.2 ABC Component

Despite the fact that the validity of using the TPB-ABC model has been confirmed by multiple studies (Dong & Hua, 2018; Qin & Song, 2022, and Zhang et al., 2021), this study tempers that conclusion. This moderation is mainly due to the energy crisis-related variables Positive Context (PC) and Negative Context (NC) which continuously showed a poor fit during the measurement model testing phase. As a result, the construct's reliability (CR) and validity of the model were possibly compromised due to the eliminated measurement items despite the fact that the model resulted in a good-fit. Despite that, the study confirms that PC and NC are direct predictors of AT and indirect predictors of ESB. As an addition to internal motives, external contexts can therefore be considered important and relevant for further research regarding energy saving behavior in times of an energy crisis.

Hypothesis 4 states that positive contexts (PC) positively impact an individual's attitude towards performing energy saving behavior. Regarding the construct PC, it became evident that 2 out of 3 measurement items showed a poor fit in the model. More specifically, the indicators: PC1 "governmental campaigns make me save energy" and PC3 "Reduced disposable income (inflation) makes me save energy at home" were removed from the PC construct, resulting in a single item construct including only the measurement item PC2 "The high energy prices make me save energy at home" remained part of the positive context. Based on this, it could be argued that individuals' energy saving behavior was particularly related to high energy prices as suggested by Webb et al. (2013) and Maqbool &

Haider (2021). This is interesting as the current high energy prices are related to (energy) scarcity and thereby to various forms of inflation. It can therefore be argued that the construct PC3 related to inflation may have been formulated in an ambiguous manner. Perhaps a more valid construct could be obtained by adding a statement that includes the installation of energy saving devices in the past into the survey. This would be in line with I&O Research (2022), who showed that the Dutch population made *energy saving changes* in their homes in the past years to reduce energy consumption. It also confirms their finding that the majority of Dutch citizens have altered their behavior to reduce energy consumption due to the 'sharply risen energy costs' (I&O Research, 2022). Moreover, it is interesting to note that no relationship was found between government campaigns (PC1) and energy saving behavior. Testing hypothesis 4 was solely based on PC1, but can be considered supported.

Hypothesis 5 states that negative context (NC) negatively impacts an individuals' energy saving behavior. Results showed that NC was a direct and negative predictor of AT ($p < 0.05$). Moreover, NC showed to be an indirect predictor of ESB. Of the construct NC, the measurement item NC1 "The price cap (energie plafond) prevents me from saving energy at home" was removed from the model as it did not contribute to reaching a fit model. However, the measurement items PC2 "Falling energy prices (will) make me use more energy at home" and PC3 "A higher income would make me use more energy" reveal a negative relationship with AT. Meaning that, both measurement items can be considered significant (negative) predictors for ESB. Moreover, comparison of the constructs PC (=.246) and NC (= -.256) reveals a comparable degree of relationship with regard to AT toward energy saving behavior. Therefore, hypothesis 5 can be considered supported.

6.3 Theoretical Framework - Factors Influencing Energy Saving Behavior.

Based on the results, this study proposes an alternative theoretical framework (figure 7) to TPB-ABC. This framework shows the influencing factors of an individual's energy-saving behavior in the Netherlands in times of an energy crisis and thereby answering the research question. Some significant adjustments of the TPB-component include the fact that SN and PBC are now tied to the variable AT rather than being directly connected to the intention to engage in a certain behavior. This is because the study found that SN and PBC appear to have only an indirect influence on ESB but have a direct effect on AT and not on ESI. The Modification Indices (MI) suggested additional paths of SN predicting AT and AT predicting PBC as this would improve the overall model fit. Moreover, because AT appeared to be the strongest indicator of ESB, it was related to ESB rather than AT to ESI. This means that, in contrast to Ajzen's (1991) TPB, ESI is not included in the model as none of the TPB components (SN, AT, PBC) showed being a strong predictor of ESI. Regarding the ABC-component, it can be observed that the PC and NC constructs are still directly related to AT as suggested in the ABC-model by Stern and Oskamp (1987). This study suggests that the PC (while relatively weak) and NC are directly related to an individual's ESB and are therefore considered relevant influences of an individual's energy-saving behavior in the

Netherlands in times of an energy crisis. More measurement items might need to be added to strengthen the PC construct.

Figure 7. Influencing Factors of Energy Saving Behavior in the Netherlands.

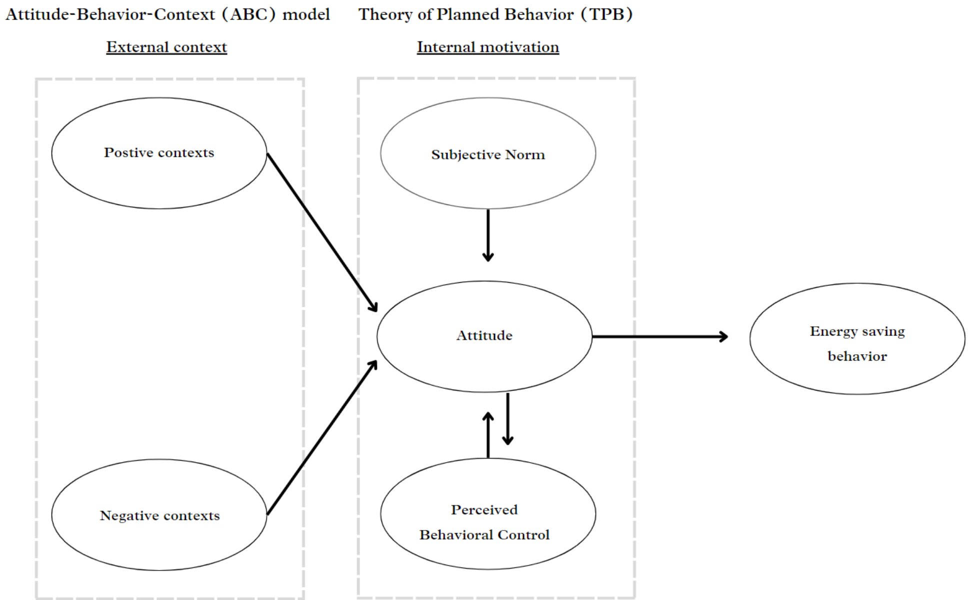


Table 9. Hypotheses Claims Based on the Results.

Hypotheses	Results
Hypothesis 1. *Positive attitude towards energy saving positively impacts an individuals' energy saving behavior.*	Supported
Hypothesis 2. *Positive subjective norms positively impact an individuals' energy saving behavior.*	Partly supported
Hypothesis 3. *High perceived behavioral control positively impacts an individuals' energy saving behavior.*	Not supported
Hypothesis 4. *Positive contexts positively impact an individual's attitude towards energy saving behavior.*	Supported*
Hypothesis 5. *Negative contexts negatively impact an individual's attitude towards energy saving behavior.*	Supported

* Based on a single-item construct

7. Conclusion

This study aimed to analyze the effect of the energy crisis on individuals' energy saving behavior within the Netherlands. The Theory of Planned Behavior (TPB) and the Attitude-Behavior-Context model (ABC) were combined adding external contexts to internal motivation in the context of energy-saving behavior. Besides the Qualtrics software bug (see limitations), the data collection went without difficulties, and N = 233 may be regarded as an adequate number of participants for this study. The data was analyzed using Structural Equation Modeling (SEM) which enabled testing causal relationships, and evaluating model fit, and thereby gaining a comprehensive understanding of the complex factors influencing human behavior (Hair et al., 2014). By adding the ABC component to TPB and relating it to energy saving behavior in times of an energy crisis, this study provided a distinct view. It aimed to answer the following research question: "*What influences individuals' energy-saving behavior in times of an energy crisis in the Netherlands?*".

First of all, this study demonstrated that the TPB proposed by Ajzen (1991) does not entirely allow for assessing individual energy-saving behavior in the Netherlands during an energy crisis. That is because of the following findings which are against the claims of TPB. First, the study showed that Intention (ESI) appeared to be no predictor for Energy Saving Behavior (ESB). Therefore, the study recommends excluding "intention" (to save more energy) from the theoretical framework and using solely "behavior" as the outcome variable. The intention to conserve more energy may be less significant now since people may be more motivated to save money than they may be to conserve (more) energy. In that regard, consideration should be given to the economic viewpoint rather than the one that is in favor of the environment. This is particularly relevant right now since the war between Russia and Ukraine has made energy scarce, driving up prices considerably and increasing the rate of inflation (Farghali et al., 2023).

Secondly, Subjective Norm (SN) and Perceived Behavioral Control (PBC) did not directly correlate with energy-saving intention or behavior. Although not in the same way that TPB proposed, Subjective Norms and Perceived Behavioral Control did appear to be direct predictors of Attitude in this study, suggesting that they are still important for understanding individuals energy-saving behavior. Furthermore, it is evident that of the three variables of TPB, Attitude is considered to be the strongest predictor of both Intention and (particularly of) Behavior. The study showed that Subjective Norm and Perceived Behavioral Control were no direct predictors of intention or behavior. However, they did appear to be predictors of Attitude and are therefore still added to the adapted theoretical framework (figure 7).

Thirdly, and related to the ABC model, the present study added to previous studies by using the construct Positive Context and Negative Contexts directly related to energy saving behavior in the Netherlands in times of an energy crisis. In the measurement model testing phase, it became clear that the Positive Context's data was problematic, resulting in a single-item construct. More measurement items might need to be added to strengthen the PC construct. By doing so, the measurement items related to governmental campaigns and inflation were removed from the model, leaving only the high energy prices as a motive to perform Energy Saving Behavior in. It is remarkable that the inflation item did not predict energy-saving behavior because, according to I&O Research (2022), the Dutch populace did cut back on consumption while inflation was present. However, this can be the effect of employing other measurements rather than consuming less energy, or perhaps the participants in the measurement items might not have made the connection between inflation and reducing energy usage. Furthermore, the Negative Context appeared to be a direct effect and negative predictor of Attitude as well as an indirect predictor of Energy Saving Behavior. All in all, it became clear that Negative Context and Positive Context are closely associated to Attitude as well as to energy-saving behavior. In that regard, the variables highlighted in this study are crucial for understanding how people conserve energy during a crisis.

To conclude, the current study presented which variables are relevant for explaining an individual's energy-saving behavior in the Netherlands in times of an energy crisis. In terms of scientific contribution, this study added to the current body of literature by applying the TPB-ABC to the specific situation of energy-saving behavior and relating it to the current energy crisis. In terms of societal relevance, this study provided knowledge on the variables to take into account when formulating regulations and policies, allowing for a more focused approach. Using this information to assess the present state of an individual's energy saving behavior and plan for future interventions is the task at hand. *"Don't let this energy crisis go to waste"*.

8. Limitations of the Study

There are several limitations to this study that need explanation. First, the survey software Qualtrics contained an error. For some respondents, the option "completely disagree" was completely removed from the survey and replaced by "completely agree". It is unknown how many participants were affected by this software defect, as just a few individuals made note of it. Participants who reported it were advised to discontinue responding to the questionnaire since those incomplete surveys were going to be deleted from the data collection. Since it cannot be said with certainty that every responder who dealt with this problem reported it, it is unclear how this may have affected the study's findings. It is advised to utilize a different, more dependable sort of software for future studies.

Secondly, for this type of analysis, the data could be considered somewhat problematic since multiple measurement items needed to be removed from the model as they resulted in a poorly fitting model. However, SEM´s MI suggested multiple additional relationships to the model which increased the model's fit and the constructs' validity. Better outcomes could be obtained with a longer set of measurement items resulting in more items reflecting the variable. As a result, the survey would have taken longer, which may lead to fewer respondents fully completing it. However, it may be extended by for instance adding 2 statements to the constructs because the current time occupation for participants was 3 to 5 minutes which is quite limited.

Thirdly, the survey contained a 4-point likert scale, meaning that the middle point or 'neutral' option was left out. This was selected as respondents may choose a midway even if their genuine view is not neutral, which is shown by Kulas & Stachowski's (2009). Moreover, in cases in which so-called 'satisficing behavior' or 'socially desirable behavior' may be favored by the participants, it may be best to omit the midpoint option (Kulas & Stachowski, 2009). This is likely to be the case for energy saving behavior. On the other hand, having a midway allows respondents to express a neutral perspective, particularly on complex issues such as energy saving behavior (Johns, 2005). Future research could also consider using a 'N/A' or an 'I don't know' option to prevent misuse of a midpoint (Kulas & Stachowski, 2009), but allowing respondents to choose a midway answer.

8. References

Abrahamse, W., & Steg, L. (2011). Factors Related to Household Energy Use and Intention to Reduce It : The Role of Psychological and Socio-Demographic Variables. *Human Ecology Review*, *18*, 30-40.

Abrahamse, W., Steg, L., Vlek, C., & Rothengatter, T. (2005). A review of Intervention Studies aimed at household energy conservation. *Journal of Environmental Psychology*, *25*(3), 273–291. https://doi.org/10.1016/j.jenvp.2005.08.002

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., & Fishbein, M. (2005). The Influence of Attitudes on Behavior. In D. Albarracín, B. T. Johnson, & M. P. Zanna (Eds.), *The handbook of attitudes* (pp. 173–221). Lawrence Erlbaum Associates Publishers

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Aydin, E., Kok, N., & Brounen, D. (2017). Energy efficiency and household behavior: The rebound effect in the residential sector. *The RAND Journal of Economics*, *48*(3), 749–782. https://doi.org/10.1111/1756-2171.12190

Baron, J. (2006). *Thinking and Deciding* (4th ed.). Cambridge: Cambridge University Press. doi:10.1017/CBO9780511840265

Bovey, W. H., & Hede, A. (2001). Resistance to organizational change: The role of cognitive and Affective Processes. *Leadership & Organization Development Journal*, *22*(8), 372–382. https://doi.org/10.1108/01437730110410099

Bundy, J., Pfarrer, M. D., Short, C. E., & Coombs, W. T. (2017). Crises and Crisis Management: Integration, Interpretation, and Research Development. *Journal of Management*, *43*(6), 1661–1692. https://doi.org/10.1177/0149206316680030

Cambefort, M. (2020). How the covid-19 pandemic is challenging consumption. *Markets, Globalization & Development Review*, *5*(1). https://doi.org/10.23860/mgdr-2020-05-01-02

Casaló, L. V., Escario, J.-J., & Rodriguez-Sanchez, C. (2019). Analyzing differences between different types of pro-environmental behaviors: Do attitude intensity and type of knowledge matter? *Resources, Conservation and Recycling*, *149*, 56–64. https://doi.org/10.1016/j.resconrec.2019.05.024

Chen, C.-fei, & Knight, K. (2014). Energy at work: Social Psychological Factors affecting energy conservation intentions within Chinese Electric Power Companies. *Energy Research & Social Science*, *4*, 23–31. https://doi.org/10.1016/j.erss.2014.08.004

Clark, C. F., Kotchen, M. J., & Moore, M. R. (2003). Internal and external influences on pro-environmental behavior: Participation in a Green Electricity Program. *Journal of Environmental Psychology*, *23*(3), 237–246. https://doi.org/10.1016/s0272-4944(02)00105-6

Cohen, M. J. (2020). Does the COVID-19 outbreak mark the onset of a sustainable consumption transition? *Sustainability: Science, Practice and Policy*, *16*(1), 1–3. https://doi.org/10.1080/15487733.2020.1740472

Conner, M., & Norman, P. (2022). Understanding the intention-behavior gap: The role of intention strength. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.923464

Conner, M., & Armitage, C. J. (1998). Extending the theory of planned behavior: A review and avenues for further research. *Journal of Applied Social Psychology*, *28*(15), 1429–1464. https://doi.org/10.1111/j.1559-1816.1998.tb01685.x

Conner, M., Godin, G., Sheeran, P., & Germain, M. (2013). Some feelings are more important: Cognitive attitudes, affective attitudes, anticipated affect, and blood donation. *Health Psychology*, *32*(3), 264–272. https://doi.org/10.1037/a0028500

Desivilya, H., Teitler-Regev, S., & Shahrabani, S. (2015). The effects of conflict on risk perception and travelling intention of young tourists. *EuroMed Journal of Business*, *10*(1), 118–130. https://doi.org/10.1108/emjb-08-2014-0025

DeWaters, J. E., & Powers, S. E. (2011). Energy Literacy of Secondary students in New York State (USA): A measure of knowledge, affect, and behavior. *Energy Policy*, *39*(3), 1699–1710. https://doi.org/10.1016/j.enpol.2010.12.049

Dong, F., & Hua, Y. (2018). Are Chinese residents willing to Recycle Express packaging waste? evidence from a Bayesian regularized neural network model. *Sustainability*, *10*(11), 4152. https://doi.org/10.3390/su10114152

Dias, R. A., Mattos, C. R., & Balestieri, J. A. P. (2004). Energy education: Breaking up the Rational Energy Use Barriers. *Energy Policy*, *32*(11), 1339–1347. https://doi.org/10.1016/s0301-4215(03)00100-9

Du, J., & Pan, W. (2021). Examining energy saving behaviors in student dormitories using an expanded theory of planned behavior. *Habitat International*, *107*, 102308. https://doi.org/10.1016/j.habitatint.2020.102308

Edvardsson, B., & Tronvoll, B. (2020). How platforms foster service innovations. *Organizational Dynamics*, *49*(3), 100721. https://doi.org/10.1016/j.orgdyn.2019.04.007

Edvardsson, B., & Tronvoll, B. (2021). Crisis behaviors as drivers of value co-creation transformation. *International Journal of Quality and Service Sciences*, *14*(5), 1–15. https://doi.org/10.1108/ijqss-01-2021-0001

Edwards, J. R., & Lambert, L. S. (2007). Methods for integrating moderation and Mediation: A general analytical framework using moderated path analysis. *Psychological Methods*, *12*(1), 1–22. https://doi.org/10.1037/1082-989x.12.1.1

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

Farghali, M., Osman, A. I., Mohamed, I. M., Chen, Z., Chen, L., Ihara, I., Yap, P.-S., & Rooney, D. W. (2023). Strategies to save energy in the context of the Energy Crisis: A Review. *Environmental Chemistry Letters*. https://doi.org/10.1007/s10311-023-01591-5

Frederiks, E. R., Stenner, K., & Hobman, E. V. (2015). Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour. *Renewable and Sustainable Energy Reviews*, *41*, 1385–1394. https://doi.org/10.1016/j.rser.2014.09.026

Gao, L., Wang, S., Li, J., & Li, H. (2017). Application of the extended theory of planned behavior to understand individual's energy saving behavior in workplaces. *Resources, Conservation and Recycling*, *127*, 107–113. https://doi.org/10.1016/j.resconrec.2017.08.030

Gatersleben, B., Steg, L., & Vlek, C. (2002). Measurement and Determinants of Environmentally Significant Consumer Behavior. *Environment and Behavior*, *34*(3), 335–362. https://doi.org/10.1177/0013916502034003004

Gârdan, I. P., Micu, A., Paştiu, C. A., Micu, A. E., & Gârdan, D. A. (2023). Consumers' attitude towards renewable energy in the context of the energy crisis. *Energies*, *16*(2), 676. https://doi.org/10.3390/en16020676

Gardner, G. T., & Stern, P. C. (2002). *Environmental problems and human behavior*. Pearson Custom Publ.

Goertzen, M. J. (2017). Introduction to quantitative research and data. Library Technology Reports, 53(4), 12-18.

Guagnano, G. A., Stern, P. C., and Dietz, T. (1995). Influences on attitude-behavior relationships: A natural experiment with curbside recycling. Environ. Behav. 27, 699–718. doi: 10.1177/0013916595275005c

Guèvremont, A., Boivin, C., Durif, F., & Graf, R. (2022). Positive behavioral change during the COVID-19 crisis: The role of optimism and collective resilience. *Journal of Consumer Behaviour*, 10.1002/cb.2083. https://doi.org/10.1002/cb.2083

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2011). An assessment of the use of partial least squares structural equation modeling in Marketing Research. *Journal of the Academy of Marketing Science*, *40*(3), 414–433. https://doi.org/10.1007/s11747-011-0261-6

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis* (Seventh edition, Pearson new international, Ser. Pearson custom library). Pearson Education Limited.

Johns, R. (2005). One size doesn’t fit all: Selecting response scales for attitude items. *Journal of Elections, Public Opinion & Parties*, *15*(2), 237–264. https://doi.org/10.1080/13689880500178849

Ibm Corp. (2013). IBM SPSS statistics for windows. 22.0. Armonk, NY: IBM Corp.

Kentas, G. (2023). Cyprus: Global energy crisis is an opportunity to tackle climate change. *Climate Change and the Future of Europe*, 19–22. https://doi.org/10.1007/978-3-031-23328-9_5

Kirk, C. P., & Rifkin, L. S. (2020). I'll trade you diamonds for toilet paper: Consumer reacting, coping and adapting behaviors in the COVID-19 pandemic. *Journal of Business Research*, *117*, 124–131. https://doi.org/10.1016/j.jbusres.2020.05.028

Kline, R. B. (2016). *Principles and practice of structural equation modeling*. The Guilford Press.

Klöckner, C. A. (2013). A comprehensive model of the psychology of environmental behaviour—a meta-analysis. *Global Environmental Change*, *23*(5), 1028–1038. https://doi.org/10.1016/j.gloenvcha.2013.05.014

I&O Research (2022, October). *Duurzaam denken wordt (langzaamaan) duurzaam doen.* I&O Research. Retrieved February 24, 2024. 2022/253

La Barbera, F., & Ajzen, I. (2021). Moderating role of perceived behavioral control in the theory of planned behavior: A preregistered study. *Journal of Theoretical Social Psychology*, *5*(1), 35–45. https://doi.org/10.1002/jts5.83

Lambert, L. A., Tayah, J., Lee-Schmid, C., Abdalla, M., Abdallah, I., Ali, A. H. M., Esmail, S., & Ahmed, W. (2022). The EU's Natural Gas Cold War and diversification challenges. *Energy Strategy Reviews*, *43*, 100934. https://doi.org/10.1016/j.esr.2022.100934

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

Liu, X., Wang, Q.-C., Jian, I. Y., Chi, H.-L., Yang, D., & Chan, E. H.-W. (2021). Are you an energy saver at home? the personality insights of household energy conservation behaviors based on theory of planned behavior. *Resources, Conservation and Recycling*, *174*, 105823. https://doi.org/10.1016/j.resconrec.2021.105823

Liu, X., Wang, C., Shishime, T., & Fujitsuka, T. (2010). Sustainable consumption: Green purchasing behaviours of urban residents in China. *Sustainable Development*, *20*(4), 293–308. https://doi.org/10.1002/sd.484

Lu, H., Zou, J., Chen, H., & Long, R. (2020). Promotion or inhibition? moral norms, anticipated emotion and employee's pro-environmental behavior. *Journal of Cleaner Production*, *258*, 120858. https://doi.org/10.1016/j.jclepro.2020.120858

Martinsson, J., Lundqvist, L.J. and Sundström, A. (2011) Energy Saving in Swedish Households. The (Relative) Importance of Environmental Attitudes. *Energy Policy*, 39, 5182-5191. https://doi.org/10.1016/j.enpol.2011.05.046

Maqbool, G., & Haider, Z. (2021). The impact of individual behavior on household energy saving. *Journal of Economic Impact*, *3*(1), 39–46. https://doi.org/10.52223/jei3012105

Milne, G., & Boardman, B. (2000). Making cold homes warmer: The effect of energy efficiency improvements in low-income homes a report to the Energy Action Grants Agency Charitable Trust. *Energy Policy*, *28*(6-7), 411–424. https://doi.org/10.1016/s0301-4215(00)00019-7

Ministerie van Binnenlandse Zaken en Koninkrijksrelaties (BZK), & Ministerie van Economische Zaken en Klimaat (EZK). (2022, April 4). *Kabinet start landelijke Energiebesparingscampagne en komt met Nationaal isolatieprogramma om 2,5 Miljoen Woningen Snel Te Isoleren*. Nieuwsbericht | Rijksoverheid.nl. Retrieved March 28, 2023, from https://www.rijksoverheid.nl/actueel/nieuws/2022/04/02/kabinet-start-landelijke-energiebesparingscampagne-en-komt-met-nationaal-isolatieprogramma-om-2.5-miljoen-woningen-snel-te-isoleren

Ministerie van Algemene Zaken. (2023, March 24). *Prijsplafond voor gas, stroom en stadsverwarming*. Koopkracht | Rijksoverheid.nl. Retrieved March 29, 2023, from https://www.rijksoverheid.nl/onderwerpen/koopkracht/plannen-kabinet-met-prijsplafond-voor-gas-en-elektriciteit

Nie, H., Vasseur, V., Fan, Y., & Xu, J. (2019). Exploring reasons behind careful-use, energy-saving behaviours in residential sector based on the theory of planned behaviour: Evidence from Changchun, China. *Journal of Cleaner Production*, *230*, 29–37. https://doi.org/10.1016/j.jclepro.2019.05.101

Oikonomou, V., Becchis, F., Steg, L., & Russolillo, D. (2009). Energy Saving and Energy Efficiency Concepts for policy making. *Energy Policy*, *37*(11), 4787–4796. https://doi.org/10.1016/j.enpol.2009.06.035

Olli, E., Grendstad, G., & Wollebaek, D. (2001). Correlates of environmental behaviors. *Environment and Behavior*, *33*(2), 181–208. https://doi.org/10.1177/0013916501332002

Ozdamar Ertekin, Z., Sevil Oflac, B., & Serbetcioglu, C. (2020). Fashion consumption during economic crisis: Emerging practices and feelings of consumers. *Journal of Global Fashion Marketing*, *11*(3), 270–288. https://doi.org/10.1080/20932685.2020.1754269

Pallant, J., (2010). SPSS survival manual: A step by step guide to data analysis using the SPSS program. 4th Edition, McGraw Hill, New York.

Park, H. S. (2000). Relationships among attitudes and subjective norms: Testing the theory of reasoned action across cultures. *Communication Studies*, *51*(2), 162–175. https://doi.org/10.1080/10510970009388516

Poortinga, W., Steg, L., Vlek, C., & Wiersma, G. (2003). Household preferences for energy-saving measures: A conjoint analysis. *Journal of Economic Psychology*, *24*(1), 49–64. https://doi.org/10.1016/s0167-4870(02)00154-x

Qin, B., & Song, G. (2022). Internal motivations, external contexts, and sustainable consumption behavior in China—based on the TPB-ABC integration model. *Sustainability*, *14*(13), 7677. https://doi.org/10.3390/su14137677

Ridder, J., E. Josten., J. Boelhouwer., & C. van Campen (2020). De sociale staat van Nederland 2020. Den Haag: Sociaal en Cultureel Planbureau (SCP) ISBN 978 90 377 0953 7.

Sheeran, P., Gollwitzer, P. M., & Bargh, J. A. (2013). Nonconscious processes and health. *Health Psychology*, *32*(5), 460–473. https://doi.org/10.1037/a0029203

Suárez-Álvarez, J., Pedrosa, I., & Lozano, L. M. (2018). Using reversed items in Likert scales: A questionable practice. *Psicothema*, *30.2*, 149–158.https://doi.org/10.7334/psicothema2018.33

Suntornsan, S., Chudech, S., & Janmaimool, P. (2022). The role of the theory of planned behavior in explaining the energy-saving behaviors of high school students with physical impairments. *Behavioral Sciences*, *12*(9), 334. https://doi.org/10.3390/bs12090334

Sütterlin, B., Brunner, T. A., & Siegrist, M. (2011). Who puts the most energy into energy conservation? A segmentation of energy consumers based on energy-related behavioral characteristics. *Energy Policy*, *39*(12), 8137–8152. https://doi.org/10.1016/j.enpol.2011.10.008

Steg, L. (2008). Promoting household energy conservation. *Energy Policy*, *36*(12), 4449–4453. https://doi.org/10.1016/j.enpol.2008.09.027

Stern, P. C., & Oskamp, S. (1987). "Managing scarce environmental resources," in Handbook of Environmental Psychology, eds D. Stokols and I. Altman (New York, NY: Wiley), 1044–1088.

Stern, P. C. (2000). New environmental theories: Toward a coherent theory of environmentally significant behavior. *Journal of Social Issues*, *56*(3), 407–424. https://doi.org/10.1111/0022-4537.00175

Stern, P. C. (1999). Information, incentives, and pro-environmental consumer behavior. *Journal of Consumer Policy*, *22*(4), 461–478. https://doi.org/10.1023/a:1006211709570

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

Szymańska, E. J., Kubacka, M., & Polaszczyk, J. (2023). Households' energy transformation in the face of the energy crisis. *Energies*, *16*(1), 466. https://doi.org/10.3390/en16010466

Trotta, G. (2018). Factors affecting energy-saving behaviours and energy efficiency investments in British households. *Energy Policy*, *114*, 529–539. https://doi.org/10.1016/j.enpol.2017.12.042

Vink, J., Edvardsson, B., Wetter-Edman, K., & Tronvoll, B. (2019). Reshaping mental models – enabling innovation through Service Design. *Journal of Service Management*, *30*(1), 75–104. https://doi.org/10.1108/josm-08-2017-0186

Wang, H., Li, J., Mangmeechai, A., & Su, J. (2021). Linking Perceived Policy Effectiveness and Proenvironmental Behavior: The Influence of Attitude, Implementation Intention, and Knowledge. *International journal of environmental research and public health*, *18*(6), 2910. https://doi.org/10.3390/ijerph18062910

Wang, S., An, Y., Xie, C., Zhang, H., & Zeng, Q. (2018). First-principles prediction of ferromagnetism in transition-metal doped monolayer aln. *Superlattices and Microstructures*, *122*, 171–180. https://doi.org/10.1016/j.spmi.2018.08.009

Webb, D., Soutar, G. N., Mazzarol, T., & Saldaris, P. (2013). Self-determination theory and consumer behavioural change: Evidence from a household energy-saving behaviour study. *Journal of Environmental Psychology*, *35*, 59–66. https://doi.org/10.1016/j.jenvp.2013.04.003

van der Werff, E., & Steg, L. (2015). One model to predict them all: Predicting energy behaviours with the norm activation model. *Energy Research & Social Science*, *6*, 8–14. https://doi.org/10.1016/j.erss.2014.11.002

Vringer, K., Aalbers, T., & Blok, K. (2007). Household energy requirement and value patterns. *Energy Policy*, *35*(1), 553–566. https://doi.org/10.1016/j.enpol.2005.12.025

Wood, W., Quinn, J. M., & Kashy, D. A. (2002). Habits in everyday life: Thought, emotion, and action. *Journal of Personality and Social Psychology*, *83*(6), 1281–1297. https://doi.org/10.1037/0022-3514.83.6.1281

Qalati, S. A., Qureshi, N. A., Ostic, D., & Sulaiman, M. A. (2022). An extension of the theory of planned behavior to understand factors influencing Pakistani households' energy-saving intentions and behavior: A mediated–moderated model. *Energy Efficiency*, *15*(6). https://doi.org/10.1007/s12053-022-10050-z

Zhang, S., Hu, D., Lin, T., Li, W., Zhao, R., Yang, H., Pei, Y., & Jiang, L. (2021). Determinants affecting residents' waste classification intention and behavior: A study based on TPB and A-B-C methodology. *Journal of Environmental Management*, *290*, 112591. https://doi.org/10.1016/j.jenvman.2021.112591

Appendix 1. Excel sheet of variables removed, maintained, added paths.

1	Std Factor Loadings			Estimate	AVE	CR	Std Factor Loadings			Estimate	AVE	CR
2	SN3	<---	SN	0,837	0,45788867	0,689413624	AT	<---	PC2	0,361	0,13032	0,13032
3	SN2	<---	SN	0,299	0,45788867	0,689413624	AT	<---	NC	-0,335	0,29812	0,24132
4	SN1	<---	SN	0,764	0,45788867	0,689413624	AT	<---	SN	0,327	0,35005	0,602
5	PC1	<---	PC	0,302	0,15995467	0,340232938	PBC1	<---	NC	-0,17	0,29812	0,24132
6	PC2	<---	PC	0,556	0,15995467	0,340232938	PBC1	<---	AT	0,45	0,36539	0,77292
7	PC3	<---	PC	0,282	0,15995467	0,340232938	ESI1	<---	SN	0,051	0,35005	0,602
8	AT3	<---	AT	0,632	0,40281133	0,669256396	ESI1	<---	PBC1	-0,124	0,01538	0,01538
9	AT2	<---	AT	0,639	0,40281133	0,669256396	ESI1	<---	AT	0,675	0,36539	0,77292
10	AT1	<---	AT	0,633	0,40281133	0,669256396	ESB	<---	ESI1	0,09	0,0081	0,0081
11	ESI1	<---	ESI	0,649	0,237459	0,463206957	ESB	<---	AT	0,596	0,36539	0,77292
12	ESI2	<---	ESI	0,326	0,237459	0,463206957	SN1	<---	SN	0,766	0,35005	0,602
13	ESI3	<---	ESI	0,43	0,237459	0,463206957	SN3	<---	SN	0,839	0,35005	0,602
14	ESB1	<---	ESB	0,704	0,385743	0,650750894	AT1	<---	AT	0,647	0,36539	0,77292
15	ESB2	<---	ESB	0,602	0,385743	0,650750894	AT2	<---	AT	0,643	0,36539	0,77292
16	ESB3	<---	ESB	0,547	0,385743	0,650750894	AT3	<---	AT	0,589	0,36539	0,77292
17	PBC3	<---	PBC	0,491	0,23724867	0,474700982	NC2	<---	NC	0,718	0,29812	0,24132
18	PBC2	<---	PBC	0,368	0,23724867	0,474700982	NC3	<---	NC	0,732	0,29812	0,24132
19	PBC1	<---	PBC	0,579	0,23724867	0,474700982	ESB1	<---	ESB	0,703	0,38781	0,65249
20	NC1	<---	NC	0,342	0,38732733	0,634429993	ESB2	<---	ESB	0,618	0,38781	0,65249
21	NC2	<---	NC	0,687	0,38732733	0,634429993	ESB3	<---	ESB	0,536	0,38781	0,65249
22	NC3	<---	NC	0,757	0,38732733	0,634429993						

Legend	
	Removed
	Maintained
	Added (MI)