Summer 2021

The role of psychological reactance in smart home energy management systems

Matthew Thomas Heatherly

THE ROLE OF PSYCHOLOGICAL REACTANCE IN SMART HOME ENERGY MANAGEMENT SYSTEMS

by

MATTHEW THOMAS HEATHERLY

A THESIS

Presented to the Graduate Faculty of the

MISSOURI UNIVERSITY OF SCIENCE AND TECHNOLOGY

In Partial Fulfillment of the Requirement for the Degree

MASTER OF SCIENCE

in

ENGINEERING MANAGEMENT

2021

Approved by:

Dr. Casey Canfield, Advisor
Dr. Denise Baker
Dr. Suzanna Long

ABSTRACT

With an ever-growing demand for energy, our increasing consumption is producing more greenhouse gases and other pollutants, impacting climate change. One approach to reducing residential energy consumption is through the use of smart energy management systems. However, automation from smart technology inherently removes a certain amount of control from the user. If loss of control is perceived as a loss of freedom, this may lead users to experience psychological reactance when using these products. A set of experiments was conducted to assess how three features of a message notification from smart home energy management systems may induce reactance in users. In the context of a hypothetical smart thermostat, the participants responded to message notifications. The phrasing of the notification was altered depending on the assigned strength of language, type of temperature change, and justification given by the smart thermostat. Reactance was measured after exposure to the notification. Results indicated more authoritative language, temperatures outside the user's comfort range, and a lack of justification from the thermostat had a significant effect on inducing reactance. Evidence suggested the presence of justification for the thermostat's operations may have caused users to be more likely to accept the thermostat's temperature change, even if that temperature was outside user preferences. This study has implications for designing smart home energy management systems to increase user acceptance and decrease potential frustrations.

ACKNOWLEDGMENTS

I would like to thank my advisor, Dr. Casey Canfield, and committee member, Dr. Denise Baker. I have never met more dedicated, passionate academics. Their feedback, support, and guidance were invaluable for the completion of this project and thesis. This project would not be the same without them and they have my sincerest gratitude.

I also acknowledge the National Institute of Food and Agriculture (NIFA) for funding this project.

TABLE OF CONTENTS

LIST OF ILLUSTRATIONS

LIST OF TABLES

1. INTRODUCTION

Global energy consumption is growing faster than the human population with each person consuming more energy each passing year (*Global electricity consumption continues to rise faster than population - Today in Energy - U.S. Energy Information Administration (EIA)*, n.d.). In fact, residential energy usage accounted for nearly 40% of energy consumption in all U.S. sectors in 2020 (*Electric Power Monthly - U.S. Energy Information Administration (EIA)*, n.d.). Of that, the average American spends 12% of their total energy expenditure on air conditioning alone (*Air conditioning accounts for about 12% of U.S. home energy expenditures - Today in Energy - U.S. Energy Information Administration (EIA)*, n.d.). An ever-growing consumption of electricity results in an increasing production of greenhouse gases from burning fossil fuels (*Energy and climate change — European Environment Agency*, n.d.). Scientists claim these greenhouse gases have been the leading cause driving decades-long global warming trends (*Causes | Facts – Climate Change: Vital Signs of the Planet*, n.d.). To further the issue, rising global temperatures create an even greater demand for energy in order to combat the heat. It is estimated that a 1.8 °F increase in the U.S.'s climate would result in 5-20% additional electricity demand for cooling alone (*Climate Impacts on Energy | Climate Change Impacts | US EPA*, n.d.).

To help resolve these issues, a variety of strategies have been used, such as educational approaches and demand response. Information-based strategies have been commonly attempted for decades. These strategies have had mixed results with individual audits and consultation methods proving more effective than historical peer comparison based methods at inducing conservation behavior (Delmas et al., 2013). Demand-response is another strategy where the price of electricity fluctuates as demand varies. Demand-response programs incentivize reducing or shifting energy usage during peak periods (*Demand Response | Department of Energy*, n.d.). However, the implementation of demand response systems comes with a few challenges, including scalability, security, and user acceptance (Yassine, 2016). One potential solution to the difficulties of implementing demand response systems is through the use of smart technology.

Smart home energy management systems help monitor energy consumption and adopt energy conservation behaviors (Helia Zandi, Teja Kuruganti, Edward Vineyard, David Fugate, 2017). They naturally work well with demand-response systems as they can be operated directly by the utility company (Batchu & Pindoriya, 2015). The automation of smart home energy management systems makes it a convenient option for people wanting to conserve energy. However, too much automation can result in users being less likely to accept the automated services as people still want to have a certain degree of control over their smart technology (Yang et al., 2018). Other factors that increase acceptance behavior include interconnectivity with other devices, reliability, and level of engagement (Batchu & Pindoriya, 2015; Helia Zandi, Teja Kuruganti, Edward Vineyard, David Fugate, 2017). With the goal of reducing energy consumption, it is vital to design smart home energy management systems such that users are more likely to use and accept them.

1.1. PSYCHOLOGICAL REACTANCE THEORY

While automated systems necessarily must remove a certain degree of control from the user to operate, this may induce psychological reactance in the user.

Psychological reactance is an emotive and cognitive response to a perceived threat to one's autonomy as described by J. W. Brehm (Brehm, 1966). As reactance theory evolved, it became known as a state comprised of two intertwined processes: the emotional response and the formation of negative thoughts. This intertwined model of state reactance was developed in studies by Dillard and Shen wherein they called the two processes Anger and Negative Cognitions (Dillard & Shen, 2005).

For reactance to be induced, a threat to one's autonomy must be present. The threat can be direct or implied (Brehm, 1989). For example, a parent telling their child to wash the dishes directly threatens the child's ability to choose whether they wanted to do the dishes while a spouse asking if they can use the family car for the evening indirectly threatens the other spouse's potential freedom to do as they please that evening. Threat to freedom has been shown to have a significant relationship with reactance and is an indication of when reactance is being experienced (Brehm, 1989; Dillard & Shen, 2005; Thiruvengada et al., 2011). Reactance was first measured via Merz's "Questionnaire for the Measurement of Psychological Reactance," which consisted of 18 items concerning situations and motivations for inducing reactance (Merz, 1983). This scale had high reliability but was lacking scale items used for determining the factors and the factor labels, according to Sung-Mook Hong (Hong & Page, 1989). In response, Hong created "Hong's Psychological Reactance Scale" (HPRS) to better measure reactance. This scale consisted of 14 items (later reduced to 11) and contained four factors, (1) Freedom of Choice, (2) Conformity Reactance, (3) Behavioral Freedom, and (4) Reactance to Advice and Recommendation. The HPRS is the standard for measuring trait reactance. Trait reactance is the predisposition a person has to experiencing psychological reactance and has been shown to have a significant positive association with state reactance (Ehrenbrink & Möller, 2018; Thiruvengada et al., 2011).

1.2. FACTORS AFFECTING REACTANCE

With a perceived threat to freedom being the driving mechanism behind reactance, there is a wide variety of factors that could potentially induce reactance. In the context of a smart home energy management system, a few such factors are the language used by the system, the temperatures the system operates within, justification provided by the system, and anthropomorphism of the system. Previous studies have shown highly authoritative language to be more likely to induce reactance than mild, polite language (Brehm, 1966; Hong & Page, 1989; Merz, 1983). When people are told they *must* act in a certain way, they feel they have no choice and experience more reactance than when told they *could* act in that same way (Reynolds-Tylus et al., 2019). Research by Miller et. al. suggested high controlling language (“have to”, “must”, “should”) resulted in an increase in reactance while low controlling language (“could”, “might”) caused a decrease in reactance (Miller et al., 2007). In the context of a persuasive robot, a study by Roubroeks et. al. involved a virtual assistant to a washing machine where the participant was tasked with programming the washing machine while the assistant provided help and feedback. The results suggested when persuasive robots use high threatening language, people experience more reactance than those that use low threatening language (Roubroeks et al., 2010).

With smart home energy management systems, the system may need to adjust the thermostat to a temperature the user might not prefer in accordance to demand-response signals. Comfort was shown to be the top reason California homeowners pursued more energy-efficient systems in one study (Knight et al., 2006). Considering the preference for comfort, operating outside the user's comfort range may result in the system's adjustments being overrode by the user (Zipperer et al., 2013). This concept of incongruent system behavior is mirrored in the persuasive robot study by Roubroeks and colleagues. The persuasive robot assistant specified whether its goals aligned with the users when programming the washing machine (i.e., saving energy vs more thoroughly washing the clothes) and gave advice in accordance with its personal goals. It was shown that when the assistant gave advice incongruent to the users goals, the user was more likely to experience reactance (Roubroeks et al., 2010).

Reactance is described as an irrational response to a perceived threat (Brehm, 1989). Due to this irrational nature of reactance, previous studies have investigated the effects of providing explanations when using persuasive language on reactance (Brehm, 1966; Ehrenbrink & Möller, 2018; Merz, 1983). These studies implied providing reasons and justifications along with suggestions resulted in lower reactance experienced in response to the suggestions. If the argument presented is reasonable to the person receiving it, they will perceive less intrusiveness.

When working with persuasive robots, anthropomorphism of the robot can also affect reactance experienced by the user according to previous studies. A study conducted by Ghazali and associates suggested information given by robots with social cues were more likely to induce reactance than the same information given as plain text (Ghazali et al., 2018b). Another study, also conducted by Ghazali and colleagues indicated negative facial expressions of persuasive robots resulted in greater reactance while positive expressions diminished reactance (Ghazali et al., 2018a).

1.3. AIMS

In a series of two studies, the effect of language, temperature, and justification (study 2 only) on psychological reactance in smart home energy management systems is evaluated. The following hypotheses are tested:

H1. The use of highly authoritative language increases user reactance. (Study 1 and 2)

H2. Making suggestions outside of the user's preferences increases user reactance. (Study 1 and 2)

H3. There will be an interaction between Language and Temperature; the use of more authoritative language and the suggestion of a temperature outside the user's preference will induce greater user reactance (Study 1 and 2).

H4. Providing an explanation decreases user reactance. (Study 2)

H5. There will be an interaction between Language, Temperature, and Justification; the use of more authoritative language, the suggestion of a temperature outside the user's preference, and the lack of justification for the temperature will induce greater reactance (Study 2).

2. STUDY I

2.1. METHODOLOGY

2.1.1. Preregistration. This study was pre-registered through Open Science Framework (OSF). All materials, data, and analysis code are posted at: https://osf.io/3cdzy.

2.1.2. Participants. Participants were recruited through Prolific, an online survey platform similar to Amazon Mechanical Turk (MTurk). Prolific has comparable data quality to MTurk with a more diverse participant pool, making it an appealing alternative (Peer et al., 2017). All participants were over 18 years old and resided in the US. Participants could be excluded from the study if they failed two of three attention checks and/or completed the study in less than 1/3 of the average completion time. Each participant was compensated $2.50 upon completion of the survey, regardless of time completed and attention check performance. This research complied with the American Psychological Association Code of Ethics and was approved by the Institutional Review Board at the University of Missouri System. Informed consent was obtained from each participant.

2.1.3. Design. Participants were asked to read and react to a message notification (ostensibly sent from the smart thermostat) about a change in their thermostat setting. The wording of the message notification (Language) was manipulated by altering the degree of authoritative language used. This was accomplished using four different phrases shown in Table 2.1.

Table 2.1: Study 1 Language Conditions

Condition	Phrase
Might	"You might want to change your thermostat setting to"
Has	"Your thermostat setting has been changed"
Will	"Your thermostat setting will be changed to"
Should	"You should change your thermostat setting to"

Each participant is assigned to one of the four language conditions. The corresponding phrase is given to them in the message notification.

The "Might" condition is low threatening language while "Should" and "Will" are highly threatening language. "Has" is also considered to be low threatening as reactance theory states the complete removal of freedom results in less reactance than the mere threat of the removal of freedom (Brehm, 1966).

The temperature mentioned in the message (Temperature) was manipulated by having a temperature suggestion either within or outside the participants' stated preference. The within, or "Congruent", temperature was the average between the participant's stated low and high temperatures rounded up to the nearest whole number. The outside, or "Incongruent", temperature is two degrees lower than the participant's stated low temperature preference.

A 4 (Language: Might, Should, Has, Will) x 2 (Temperature: Congruent, Incongruent) between-subjects factorial design was used. Participants were randomly assigned to each condition. The outcome variables were the three aspects of reactance, Negative Cognitions, Anger, and Threat to Freedom.

2.1.4. Procedure. First, participants reported if they personally use a thermostat at home. Participants who responded that they did were asked to indicate what their highest and lowest thermostat setting preferences were on cold winter days. Participants who indicated they did not use a home thermostat were also asked to provide this information, but it was rephrased slightly as: “While you do not use a thermostat in your home, we would like you to answer the following questions as if you were to use one:”. Participants were then asked how important their temperature preferences were to them. After indicating their preferred temperatures, participants were presented with a short definition of smart technology, followed by a description of a theoretical smart thermostat that could make adjustments based on “setting preferences as well as past utility data from similar homes, external environmental conditions, and scientific data about thermal comfort.” (see OSF preregistration for full text: https://osf.io/3cdzy) Participants were then asked to imagine that they received one of these thermostats from their utility company and were now setting it up for use in their own home. They were asked to choose one of two operating modes, “Comfort mode” or “Green mode.” Comfort mode was described as prioritizing user comfort, while Green mode was described as prioritizing energy conservation. To assess attention, participants were asked three questions about what they read (see OSF preregistration for the attention checks: https://osf.io/3cdzy).

After completing the set-up and attention check questions, Participants were asked to imagine that the system was now up and running and that they just received a system notification via their smart phone. Participants were randomly assigned to view one of eight system notifications that varied across two dimensions: Language and Temperature as described in Section 2.2. Participants were shown the experimentally manipulated portion of the message notification as an image (see Figure 2.1 for example).

Thank you. Next, we'd like you to imagine that you set-up the smart thermostat in your home and you installed the app on your mobile device so that you receive system notifications. You receive the following notification:

After opening the notification, you see the rest of the message:

"It is currently 50 °F with humidity of 45% and wind speeds of 6 mph. Based on current information, **you should change** your thermostat setting to **68 °F**."

Figure 2.1: Example Message Notification with Conditions Language = Should, Temperature = Incongruent

The image was accompanied by standard text, which restated the experimentally manipulated portion and added a statement about the outdoor weather conditions that was the same for all participants. The image was included to increase realism, but due to potentially small screen sizes for some participants, the full text was provided in a standard form to ensure readability.

Figure 2.1 shows the message notification a participant assigned to the "Should" and "Incongruent" Language and Temperature conditions, respectively. This example uses a stated low temperature preference of 70 °F for the "Incongruent" temperature suggestion. Following the message notification, participants completed a state reactance measure consisting of a thought listing exercise to assess Negative Cognitions, a four-item Anger scale, and a four-item Threat to Freedom scale (Dillard & Shen, 2005). A single item Negative Cognitions scale was also used (Dillard et al., 2018). Participants then completed the 11-item Hong's Psychological Reactance Scale (HPRS) for trait reactance measurement and, finally, provided demographic information (Hong & Page, 1989).

2.1.5. Measures. The primary outcome variable in Study 1 was state reactance, which was measured immediately after exposure to the message notification. Consistent with Dillard & Shen (2005), state reactance was measured across three dimensions: (1) negative cognitions (via 2 measurement approaches), (2) anger, and (3) threat to freedom. In the analysis, these dimensions are used as separate outcome variables.

Negative cognitions are the negative thoughts (e.g., attitudes, beliefs, perceptions) that form in an individual when experiencing state reactance. Negative cognitions were measured using an open-text, free form thought listing question from Dillard & Shen (2005), "Now, thinking about what you just read, please answer the following questions. (The message is provided again for your reference.)." To analyze the open text response, the sentiment analysis program, SÉANCE, was used. SEANCE is a form of natural language processing (NLP) that uses indices to analyze text and assign a sentiment score with values ranging from 0 (no negative terms in the text) to 1 (all terms in the text are negative), which is referred to as "Negative Cognitions (NLP)".

In addition, negative cognitions were measured using a single item with a 5-point Likert scale (Dillard et. al., 2018) which is referred to as "Negative Cognitions (Likert)". The Likert scaled item was "Overall, I would describe my thoughts toward the thermostat as:" with 1 = "Extremely Positive" and 5 = "Extremely Negative". These two approaches are treated as separate outcome variables.

Anger is the emotional response felt by the participant and is distinct from negative cognitions, for example, someone can think that something is bad (negative cognition) but they may not be angry about it (emotional response). Anger was measured using a four-item scale from Dillard & Shen (2005). The scale contained items such as "The amount of anger I feel after the above message is:" and "The amount of annoyance I feel after seeing the above message is:" with anchors set from 1 = "None at all" to 5 = "A great deal" on a Likert scale.

Threat to freedom measures the degree to which an individual perceives their autonomy as being threatened. It was measured using a four-item scale from Dillard & Shen (2005). The scale included items such as "The thermostat tried to make a decision for me" and "The thermostat threatened my freedom to choose" with anchors set from 1 = "Strongly Disagree" to 5 = "Strongly Agree" on a Likert scale.

In addition to state reactance, trait reactance was also measured. Where state reactance is used to determine the immediate response an individual has to a stimulus, trait reactance measures individual differences in predisposition to experience reactance.

Individuals with a higher trait reactance, are more likely to experience state reactance (Reynolds-Tylus, 2019). This was measured using the Hong Psychological Reactance Scale which contains 11 items such as "I become angry when my freedom of choice is restricted" and "I become frustrated when I am unable to make free and independent decisions" where 1 = "Strongly disagree" and 5 = "Strongly agree" on a Likert scale (Hong & Page, 1989).

In addition, the survey measured demographic information including age, gender, and education. Age was measured via an open text box that restricts answers to only numbers ranging from 18-120 years. The gender options were "Male", "Female", "Nonconforming", and "Prefer Not to Answer". The education options were "High school or less", "Some college", "Undergraduate degree", and "Graduate or professional degree".

2.1.6. Sample. A total of 252 participants were recruited (M = 53%, F = 46%, Nonconforming = 0.5%, Not specified = 0.5%). Of the participants 62% were white, 13% Asian, 8% Black/African American, 8% Hispanic, 5% Racially Mixed, and the remaining 4% reported "Other". Participants were aged 18 to 68 years (M = 31.1, SD = 10.9) with 88% being college educated and the remaining 12% at least having attained a high school education. The participants were recruited from 43 different states with 90% of participants reported using a thermostat in their homes. None of the participants were removed from the analysis for failing attention checks or completing the survey too quickly.

2.1.7. Analysis. A series of ANOVAs and ANCOVAs were used to test the hypotheses. Eight models in total were constructed. Two-way ANOVAs were performed for Negative Cognitions (NLP and Likert), Anger, and Threat to Freedom with these reactance measures being treated as the dependent variables. In the ANOVAs, Language and Temperature were treated as the independent variables. ANCOVAs were also performed for each reactance measure. Each reactance measure had its own model consisting of Language and Temperature as the independent variables and trait reactance, the mode chosen by the participant, age, gender, and education treated as covariates.

This analysis deviates from the analysis outlined in the preregistration in that ANOVAs and ANCOVAs were used in place of multiple linear regression models. This change was made as ANOVAs are more typically used in studies relating to reactance. ANOVAs were also more appropriate for the grouping structure of the experimental conditions.

2.2. RESULTS

For Negative Cognitions (NLP), the output scores from SÉANCE were used as the results for the thought listing exercise. Scores from the single Likert-scaled Negative Cognitions measure were used as the results for Negative Cognitions (Likert). For Anger and Threat to Freedom, the scores were calculated by taking the average for each 4-item scale.

Mean composite scores for the natural language processing measure ranged from 0 to 0.25 with higher scores representing the presence of more negative thoughts. The NLP measure had a calculated skewness of 2.5, indicating high skew (>1) toward low negative cognitions. Mean composite scores for the single-item Likert scale measure ranged from 1 to 5, with higher score representing more negative thoughts toward the thermostat. The Likert measure had a skewness of 0.63, indicating a moderate skew (between 0.5 and 1) toward low negative cognitions.

The 4-item scale for Anger had high internal validity (Cronbach's $\alpha = 0.93$). Mean composite scores ranged from 1 to 5 with higher scores representing a greater amount of anger. Anger had a calculated skewness of 2.3, indicating high skew toward low anger.

The 4-item scale for Threat to Freedom had acceptable internal validity (Cronbach's $\alpha = 0.73$). Mean composite scores ranged from 1 to 5 with higher scores representing a greater perceived threat to freedom. Threat to Freedom had a calculated skewness of 0.97, indicating a moderate skew toward low perceived threat to freedom.

Additional information about the reactance measures can be found in Table 2.2 and Table 2.3. Table 2.2 contains the means, standard deviation, and number of participants sorted by condition assignment. Table 2.3 depicts the Pearson Product-Moment Correlations between the reactance measures, group assignments, and demographic information.

A series of two-way ANOVA's were conducted using Language and Temperature as the independent variables and each of the four reactance measures as dependent variables. Table 2.4 shows results of each test, including effect sizes, as well as observed power, which indicated that the tests were sufficiently powered to detect any effects.

There was no main effect of Language on any of the reactance measures. As such, hypothesis 1 was not supported, that is, participants in the more authoritative language conditions did not experience greater reactance than other participants.

There was a main effect of Temperature on the Likert Negative Cognition measure, but not on the NLP Negative Cognition measure nor on Anger or Threat to Freedom (see Table 2.4). As such, hypothesis 2 was partially supported, that is, participants in the incongruent conditions reported feeling more negative thoughts about the thermostat than participants in the congruent conditions.

Table 2.2: Summary of Reactance by Condition

	Notification Type							
Language	Might		Has		Will		Should	
Temperature	Con (N=28)	Incon (N=35)	Con (N=28)	Incon (N=34)	Con (N=33)	Incon (N=29)	Con (N=37)	Incon (N=26)
Negative Cognitions (NLP)								
M	0.02	0.02	0.02	0.04	0.02	0.03	0.01	0.02
(SD)	(0.04)	(0.04)	(0.05)	(0.05)	(0.03)	(0.05)	(0.02)	(0.06)
Negative Cognitions (Likert)								
M	2.39	2.34	2.30	2.59	2.02	2.58	2.29	2.47
(SD)	(0.74)	(0.91)	(0.85)	(1.09)	(0.93)	(0.86)	(0.90)	(0.90)
Anger								
M	1.45	1.34	1.22	1.53	1.34	1.69	1.39	1.48
(SD)	(0.70)	(0.61)	(0.34)	(0.82)	(0.53)	(0.99)	(0.84)	(0.66)
Threat to Freedom								
M	2.29	2.12	2.26	2.66	2.40	2.40	2.28	2.39
(SD)	(0.74)	(0.65)	(0.56)	(0.76)	(0.66)	(0.85)	(0.83)	(0.68)

Con and Incon represent the “Congruent” and “Incongruent” Temperature conditions, respectively.

Finally, hypothesis 3 was not supported, that is, there were no significant interactions between Language and Temperature on any of the reactance measures. While the lack of significant effect from either Language or Temperature indicated a probable lack of significant interaction, the interaction was included in another ANOVA. The results showed the interaction did not have a significant effect on reactance.

Table 2.3: Pearson Product-Moment Correlations for Independent Variables, Reactance Measures, and Demographics

Group/ Measure	1	2	3	4	5	6	7	8	9	10	11	12	13
Reactance													
1. Negative Cognitions (NLP)	-												
2. Negative Cognitions (Likert)	0.17*	-											
3. Anger	0.12	0.59*	-										
4. Threat to Freedom	0.02	0.48*	0.62*	-									
Language													
5. Might	0	0	-0.03	-0.12	-								
6. Has	0.09	0.05	-0.04	0.08	-	-							
7. Will	-0.02	-0.07	0.05	0.04	-	-	-						
8. Should	-0.07	0.02	0.02	-0.01	-	-	-	-					
Temperature													
9. Incon	0.12	0.14*	0.11	0.05	-	-	-	-	-				
Demographic													
10. Hong	0.03	0.23*	0.26*	0.25*	-0.02	-0.01	0.01	0.02	0.04	-			
11. Mode: Green	-0.04	-0.06	-0.18*	-0.14*	-0.02	-0.07	0.01	0.08	-0.01	0.05	-		
12. Age	-0.01	0.1	0.14*	0.16*	0.02	-0.01	-0.04	0.03	0.08	-0.13*	-0.21*	-	
13. Gender: Male	-0.02	-0.14*	0.01	0.02	0.08	-0.02	-0.01	-0.04	-0.02	0.03	-0.04	-0.1	-
14. Education: College	-0.12	0.12	0.11	0.17*	-0.05	0.09	-0.02	-0.02	-0.02	-0.02	0.11	0.01	-0.01

$p < 0.05$ '*'. The binary categorical variables Temperature, Education, Gender, and Mode are represented by only one of their groups to reduce redundancy in the table.

Table 2.4: ANOVA Main Effects

Predictor	Reactance Measure	Sum of Squares	df	Mean Square	F	p	partial $\eta 2$	Observed Power
Language	Negative Cognitions (NLP)	0.01	3	0.00	0.88	0.451	0.012	0.053
	Negative Cognitions (Likert)	1.12	3	0.37	0.46	0.713	0.005	0.050
	Anger	0.52	3	0.17	0.36	0.782	0.005	0.050
	Threat to Freedom	2.20	3	0.73	1.45	0.230	0.019	0.055
Temperature	Negative Cognitions (NLP)	0.01	1	0.01	3.88	0.050	0.016	0.057
	Negative Cognitions (Likert)	3.57	1	3.57	4.40	0.037	0.018	0.059
	Anger	1.61	1	1.61	3.36	0.068	0.014	0.056
	Threat to Freedom	0.47	1	0.47	0.93	0.336	0.004	0.050
Language x Temperature	Negative Cognitions (NLP)	0.00	3	0.00	0.19	0.902	0.002	0.050
	Negative Cognitions (Likert)	2.85	3	0.95	1.17	0.320	0.014	0.053
	Anger	2.11	3	0.70	1.47	0.223	0.018	0.055
	Threat to Freedom	2.74	3	0.91	1.80	0.148	0.022	0.057
Residuals	Negative Cognitions (NLP)	0.48	242	0.00				
	Negative Cognitions (Likert)	196.07	242	0.81				
	Anger	116.03	242	0.48				
	Threat to Freedom	122.91	242	0.51				

As shown in Table 2.3, a few of the demographic measures had significant correlations with the reactance measures. To further probe the relation between the independent variables and the dependent variables, a two-way ANCOVAs was conducting using age, gender, education, trait reactance, and mode as covariates. Results indicate there was still no main effect of Language and no interactions between Language and Temperature. They also indicated that the main effect of Temperature was fully explained by individual differences in Trait Reactance, that is, when controlling for Trait Reactance, the effect of temperature on the Likert Neg Cog measure was no longer significant (refer to Appendix A, Table A.1). Trait reactance having an association with state reactance in the analysis is in line with previous studies as discussed in Section 1.3.

To reduce the likelihood of Type I errors, robustness analysis was conducted by testing other analytical approaches. As the data for the reactance measures were substantially skewed (see section 3.1.), log transformations were performed on the reactance measures that were highly skewed, Anger and Negative Cognitions (NLP), and the ANOVAs were performed again. Due to the extreme skew, the log transformations were unable to normalize the data for neither the Anger nor the Negative Cognitions (NLP) scores and non-normalized data violates the assumptions for performing an ANOVA. The models were also not improved by the transformations (see Appendix A, Table A.2 for the analysis).

As Anger was the most skewed state reactance measure, a quantile regression analysis was performed as quantile regressions are more robust and can show significant relationships even for heavily skewed data. The quantile regression featured Anger as the outcome variable with Language and Temperature as the predictors. However, the quantile regression did not yield different results compared to the standard ANOVA analysis (Appendix A, Table A.3).

To further analyze Anger scores, Anger was transformed into a binary variable with scores of one being converted to zero to represent “No Anger Experienced” (N = 133) and scores greater than one being converted to one to represent “Any Anger Experienced” (N = 119). A logistic regression was then performed on the binary Anger scores. The logistic regression for binary Anger did not produce different results either (Appendix A, Table A.4).

Finally, the data was split evenly into two groups: low trait reactance and high trait reactance. A series of ANOVAs was again performed for both groups. Even in the most ideal condition for reactance induction (High Trait Reactance, “Incongruent” Temperature, and “Should” or “Will” Language conditions), no evidence of any significant effect between the reactance measures and the experimental conditions was found (Appendix A, Tables A.5 and A.6).

After considering potential issues with Study 1’s design in inducing reactance, the experiment was redesigned for a second study. The justification given to the participant in the message notification was the main suspect for why participants reported experiencing low reactance. A new experiment was designed in order to test whether the justification provided by the smart thermostat influenced user reactance.

3. STUDY II

3.1. METHODOLOGY

3.1.1. Preregistration. This study was pre-registered through Open Science Framework (OSF). All materials, data, and analysis code are posted at: https://osf.io/tw2vp

3.1.2. Participants. Similar to Study 1, participants were recruited through Amazon Mechanical Turk. Study 2 was limited to U.S. citizens, 18 years of age or older. Participants from Study 1 were excluded from Study 2. Participant results could be excluded if they failed 2 of 3 attention checks and / or finished the survey in less than 1/3 of the average time taken to complete the survey. Each participant was paid $2.50 upon completion of the survey, regardless of completion time and attention check performance. This research complied with the American Psychological Association Code of Ethics and was approved by the Institutional Review Board at the University of Missouri System. Informed consent was obtained from each participant.

3.1.3. Design. Participants were asked to read and react to a message notification, as in Study 1. The message notification was identical to the one featured in Study 1 except for a few alterations. The degree of authoritative language in the message was manipulated, however, the condition featuring the phrase “you should change your thermostat setting to” was replaced with “you must change your thermostat setting to”. “Must” was included due to the desire of wanting a stronger language condition. It replaced “Should” as they filled similar roles as being the high authoritative language condition and having 5 Language conditions would not have been as viable. The temperature manipulation was unaltered from Study 1.

In addition, the message notification was further manipulated by either including or leaving out a justification for the thermostat's operations. This was accomplished by showing the participants the phrase: "It is currently 50 °F with humidity of 45% and wind speeds of 6 mph" in the "Transparent" condition while those in the "Intransparent" condition were not shown the phrase. The presence of a justification for all participants in Study 1 may have been a factor in the overall low amount of reactance experienced. As discussed in Section 1.3., providing justification has been shown in previous studies to decrease reactance.

A 4 (Language: "Might", "Has", "Will", "Must") x 2 (Temperature: "Congruent", "Incongruent") x 2 (Justification: "Transparent", "Intransparent") between-subjects factorial design was used. Participants were randomly assigned to each condition.

The measured outcome variables in this study were Negative Cognitions, Anger, and Threat to Freedom. These were assessed after the participants were given the message notification.

3.1.4. Procedure. The survey flow in the Qualtrics survey remained largely the same from Study 1, except for a few changes. In Study 2, the smart thermostat described and used throughout the survey was anthropomorphized, a second message notification was added, and behavioral intention questions were included.

The smart thermostat was anthropomorphized by giving it a gender-neutral name, SEM (Smart Energy Management), and providing an image of a thermostat with humanoid characteristics and a neutral expression in the thermostat description (refer to Figure 3.1). After the thermostat's name was told to the participants, the thermostat was exclusively referred to as SEM for the remainder of the survey. This was done to potentially induce more reactance using studies by Ghazali as reference (Ghazali et al., 2018b, 2018a).

The second message notification was added to create a scenario that would potentially increase the chance of participants experiencing reactance. This message notification was given after participants completed the reactance measurement scales for the first message notification. It used the same format as the first message notification and retained the same Language and Justification assignments for each participant. For example, if a participant were assigned to the "Will" and "Transparent" conditions for the first message notification, they would keep those assignments for the second. Temperature was altered by assigning everyone to an enhanced "Incongruent" condition wherein the thermostat would recommend a temperature suggestion three degrees Fahrenheit lower than the participants' lowest preferred temperature. Reactance was assessed using the same scales as the first message notification following the second message notification.

To assess behavioral intention, participants were asked "How likely are you to accept the new temperature: [TEMP]" after being given the reactance measurement scales. This question was asked after both message notifications.

3.1.5. Measures. The measures in Study 2 are identical to the measures in Study 1 except for a few modifications (refer to Section 3.4.). The thought listing exercise and corresponding natural language processing measure for negative cognitions was not included in Study 2. In addition, behavioral intention questions were added after each message notification. Behavioral intention was measured with a single item: "How likely are you to accept the new temperature: [TEMP]" with anchors set from 1 = "Extremely Unlikely" to 5 = "Extremely Likely".

Figure 3.1: Image of the Smart Thermostat, SEM, in the Thermostat Description of the Survey

3.1.6. Sample. For the experiment, 500 participants were recruited with 51% being male, 46% female, 2% non-conforming, and 1% not having specified. Of the participants 63% where white, 19% Asian, 6% Black/African American, 5% Hispanic, 5% racially mixed, less than 1% were Native American / Alaskan Native, and less than 1% reported "Other". Participants were 18 to 78 years old (M = 33, SD = 11) with 89% having attained at least some level of college education and the remaining 11% having a high school education or lower. There was representation from 48 different states in the sample with 92% of participants reported using thermostats in their homes. None of the participants' responses were excluded because of failed attention checks or finishing the survey too quickly.

3.1.7. Analysis. To test the hypotheses, a series of ANOVAs and ANCOVAs were used. Six total models were constructed. Each reactance measure (Negative Cognitions, Anger, and Threat to Freedom) was treated as the dependent variable in its own ANOVA model. The independent variables for these models were Language, Temperature, and Justification. In addition, each reactance measure had their own corresponding ANCOVA model. These models also had Language, Temperature, and Justification as the independent variables but included covariates such as trait reactance, the thermostat mode chosen by the participant, age, gender, and education.

The analysis deviated from the preregistration in that ANOVAs and ANCOVAs were used instead of linear regressions. As in Study 1, this was done to mirror analytical methods used in other reactance research and for ease of reporting results.

3.2. RESULTS

3.2.1. Reactance Measurement. For Anger and Threat to Freedom, the average score across their respective 4-item scales was used to represent each measure. Negative Cognitions was measured using a single item, so the results from that item were used to represent the measure.

As reported in Table 3.2, all three reactance measures were highly correlated with each other. Participants who experienced more anger also tended to experience more threat to freedom as well as more negative cognitions (where higher negative cognition scores represent more negative thoughts).

Negative Cognitions mean composite scores ranged from 1 to 5. With scores below 3 representing positive thoughts toward the thermostat, participants in most conditions reported experiencing positive thoughts as shown in Table 3.1. However, in the conditions "Will/Incongruent/Intransparent" and "Must/Incongruent/Intransparent", the means were over 3, signifying participants in those conditions reported experiencing more negative thoughts. Negative Cognitions had a calculated skewness of 0.37, indicating an approximately symmetric distribution.

Mean composite scores for Anger varied from 1 to 5. Anger was highly skewed to the right (skewness = 1.76), indicating most participants reported experiencing relatively low Anger across most groups. Participants in the groups expected to experience higher levels of reactance ("Must", "Will", "Incongruent", and "Intransparent") did have greater scores for Anger compared to the expected low reactance groups, shown in Table 3.1. Anger had an acceptable internal scale consistency (Cronbach's $\alpha = 0.94$).

Threat to Freedom mean composite scores ranged from 1 to 5. Threat to Freedom had a moderate right skew (skewness = 0.59). Similar to the other reactance measures, average scores were relatively low across most groups with the expected high reactance inducing groups reporting greater scores on average (refer to Table 3.1). Threat to Freedom had an acceptable internal scale consistency (Cronbach's $\alpha = 0.80$).

3.2.2. Effect of Language. As reported in Table 3.2, the "Must" language condition was positively correlated with Anger, Threat to Freedom, and Negative Cognitions. This suggests that the "Must" condition was associated with higher state reactance across all three measures. Significant correlations were found between "Might" and both Anger ($r = -0.17$, $p < 0.001$) and Threat to Freedom ($r = -0.25$, $p < 0.001$). A significant correlation was also found between "Has" and Negative Cognitions (r = -0.09, p = 0.04). There were no significant correlations between “Will” and the reactance measures.

Table 3.1: Means and Std. Dev. for Reactance by Group Assignment

Notification Type				Negative Cognition		Anger		Threat to Freedom	
Language	Temperature	Justification	N	M	(SD)	M	(SD)	M	(SD)
Might	Con	Trans	30	2.30	(0.70)	1.16	(0.30)	2.17	(0.57)
		Intrans	29	2.48	(0.78)	1.44	(0.66)	2.22	(0.80)
	Incon	Trans	43	2.53	(0.80)	1.37	(0.50)	2.09	(0.73)
		Intrans	23	2.78	(0.95)	1.55	(0.92)	2.50	(0.93)
Has	Con	Trans	29	2.10	(0.77)	1.09	(0.27)	2.37	(0.68)
		Intrans	35	2.54	(0.70)	1.54	(1.08)	2.36	(0.85)
	Incon	Trans	38	2.42	(0.92)	1.59	(0.90)	2.57	(0.72)
		Intrans	22	2.95	(0.90)	1.82	(0.81)	2.51	(0.85)
Will	Con	Trans	23	2.22	(0.80)	1.35	(0.60)	2.39	(0.35)
		Intrans	34	2.41	(0.86)	1.47	(0.62)	2.57	(0.79)
	Incon	Trans	40	2.43	(0.93)	1.51	(0.84)	2.49	(0.71)
		Intrans	29	3.14	(0.95)	2.26	(1.12)	3.09	(0.89)
Must	Con	Trans	25	2.60	(0.91)	1.66	(0.72)	2.66	(0.76)
		Intrans	44	2.89	(1.02)	1.83	(0.90)	2.97	(0.90)
	Incon	Trans	24	2.92	(1.14)	2.33	(1.15)	3.22	(0.95)
		Intrans	32	3.47	(1.05)	2.26	(1.17)	3.26	(1.02)

The evidence supports an effect of language (H1). Language was found to have a significant effect on Negative Cognitions, Anger, and Threat to Freedom (refer to Table 3.3). A Tukey post-hoc test found that the “Must" condition was significantly different from the other language conditions, which were not significantly different from each other (see Figure 3.2). The correlations and ANOVA suggest participants in the most authoritative condition, “Must”, experienced the greatest amount of reactance while the other conditions were not significantly different from one another.

Table 3.2: Pearson Product-Moment Correlations for Main Effects, Reactance Measures, and Demographics

Group/ Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Reactance															
1. Negative Cognitions	-														
2. Anger	0.57*	-													
3. Threat to Freedom	0.51*	0.66*	-												
Language															
4. Might	-0.07	-0.17*	-0.25*	-											
5. Has	-0.09*	-0.08	-0.08	-	-										
6. Will	-0.05	0.01	0.03	-	-	-									
7. Must	0.22*	0.24*	0.30*	-	-	-	-								
Temperature															
8. Incongruent	0.16*	0.18*	0.11*	-	-	-	-	-							
Justification															
9. Intransparent	0.21*	0.16*	0.15*	-	-	-	-	-	-						
Misc.															
10. Education	0.05	0.09	0.14*	0.06	-0.06	0.01	0	0.05	0	-					
11. Gender	0.01	0.03	0.04	-0.01	0	-0.03	0.04	0.04	-0.01	-0.09	-				
12. Mode	-0.10*	-0.17*	-0.18*	-0.02	0.01	0.02	-0.01	0.03	-0.08	-0.04	0.01	-			
13. Age	0.09*	0.18*	0.10*	0.08	-0.10*	0	0.01	0.04	0.07	0.16*	-0.06	-0.13*	-		
14. Accept Temp	-0.63*	-0.57*	-0.40*	-0.03	0.06	0.03	-0.07	-0.19*	-0.11*	-0.02	0	0.15*	-0.15*	-	
15. Trait Reactance	0.14*	0.31*	0.32*	-0.05	-0.02	0.09	-0.01	0.05	-0.01	0.02	0.06	-0.14*	0	-0.16*	-
16. Preference Importance	0	0.15*	0.07	0.01	0	-0.01	0	-0.01	0.11*	0.04	-0.04	-0.17*	0.18*	-0.13*	0.03

$p < 0.05$ '*'. The binary categorical variables Temperature, Justification, Education, Gender, and Mode are represented by only of their groups to reduce redundancy in the table.

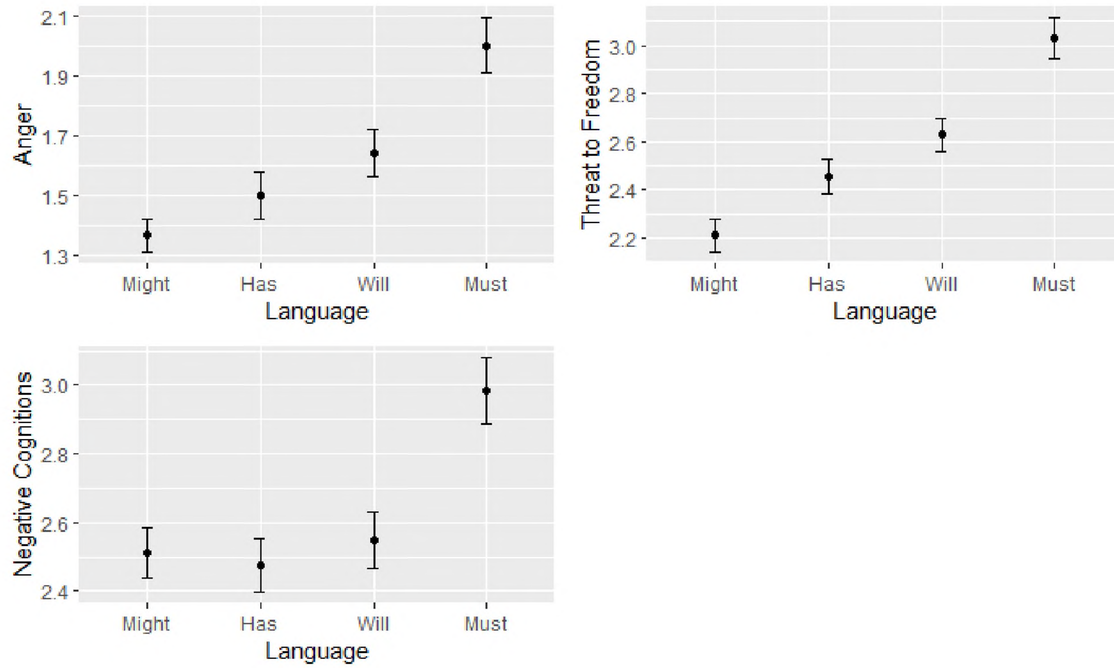

Figure 3.2: Mean and Two Standard Errors of Reactance Scores by the Language Conditions (Might vs Has vs Will vs Must)

3.2.3. Effect of Temperature. As reported in Table 3.2, the Incongruent condition was positively correlated with Anger, Threat to Freedom, and Negative Cognitions. Conversely, the "Congruent" condition was negatively correlated with all three reactance measures.

The evidence supports an effect of Temperature (H2). The ANOVA (Table 3.3) indicates the manipulation of Temperature was found to have a significant effect on Anger, Threat to Freedom, and Negative Cognitions. A post-hoc Tukey test further showed "Incongruent" was significantly different from "Congruent" (further shown in Figure 3.3). This suggests that participants given a temperature condition outside their preferred range reported feeling more reactance than those given a temperature within their preferences.

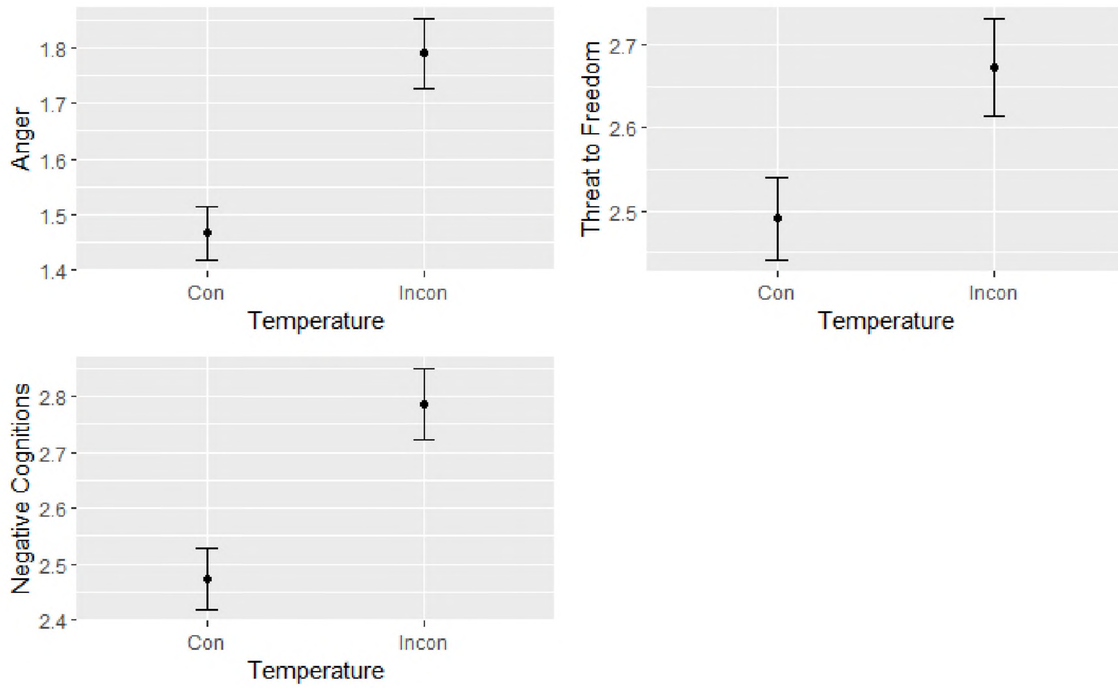

Figure 3.3: Mean and Two Standard Error of Reactance Scores by the Temperature Conditions (Congruent vs Incongruent)

3.2.4. Effect of Justification. Shown in Table 3.2, the "Intransparent" condition was positively correlated with Anger, Threat to Freedom, and Negative Cognitions. Meanwhile, "Transparent" was negatively correlated with the reactance measures. The evidence supports an effect of Justification (H4). Results from the ANOVA (Table 3.3) suggest the manipulation of Justification had a significant effect on all three reactance measures. Post-hoc tests further showed a significant difference between "Transparent" and "Intransparent" (refer to Figure 3.4). This implies participants who were not given an explanation for the thermostat's suggestions reported feeling more reactance than those that were given an explanation.

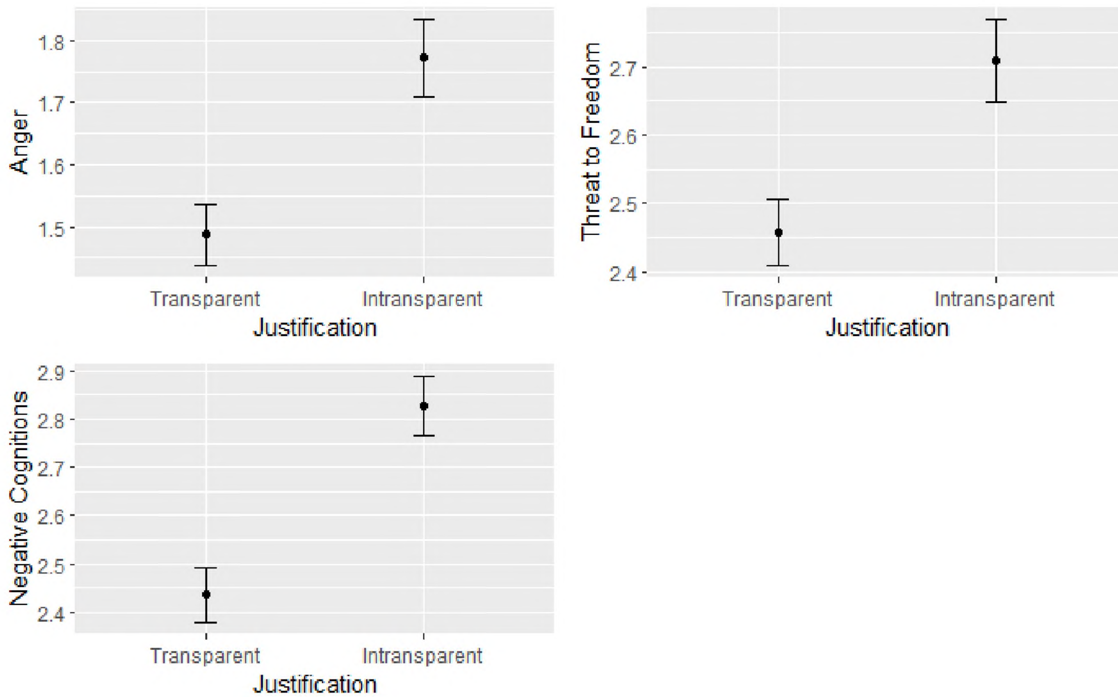

Figure 3.4: Mean and Two Standard Error of Reactance Scores by the Justification Conditions (Transparent vs Intransparent)

An interaction effect between the experimental conditions was expected; however, none was found. As shown in Table 3.3, none of the interactions were significant in the ANOVA's for any of the reactance measures. Interaction plots were also created to examine potential interactions (Figure 3.5-Figure 3.7). The interaction plots were parallel, and most conditions were not significantly different from the other in the plots except for "Will/Incongruent".

3.2.5. Analysis of the Second Message Notification. With all participants being assigned to the "Incongruent" Temperature condition in the second message notification, there were a few notable effects. Namely, in the ANOVA's for the second message notification (refer to Table 3.4), Temperature was not significant. In this case, all participants responded to the same Temperature change in the message notification.

Table 3.3: Main Effects ANOVAs for Message Notification 1

Predictor	Reactance Measure	Sum of Squares	df	Mean Square	F	p	partial $\eta 2$
Language	Negative Cognitions	21.21	3	7.07	8.88	< 0.001	0.044
	Anger	27.99	3	9.33	13.58	< 0.001	0.070
	Threat to Freedom	5.30	3	1.77	8.88	< 0.001	0.117
Temperature	Negative Cognitions	14.04	1	14.04	17.64	< 0.001	0.047
	Anger	15.22	1	15.22	22.16	< 0.001	0.054
	Threat to Freedom	3.51	1	3.51	17.64	< 0.001	0.023
Justification	Negative Cognitions	19.11	1	19.11	24.00	< 0.001	0.047
	Anger	9.28	1	9.28	13.51	< 0.001	0.027
	Threat to Freedom	4.78	1	4.78	24.00	< 0.001	0.015
Language x Temperature	Negative Cognitions	0.77	3	0.26	0.32	0.808	0.002
	Anger	2.27	3	0.76	1.10	0.348	0.007
	Threat to Freedom	0.19	3	0.06	0.32	0.808	0.005
Language x Justification	Negative Cognitions	1.42	3	0.47	0.59	0.620	0.004
	Anger	2.71	3	0.90	1.31	0.269	0.008
	Threat to Freedom	0.35	3	0.12	0.59	0.620	0.009
Temperature x Justification	Negative Cognitions	1.67	1	1.67	2.10	0.148	0.004
	Anger	0.01	1	0.01	0.02	0.892	0.000
	Threat to Freedom	0.42	1	0.42	2.10	0.148	0.001
Language x Temperature x Justification	Negative Cognitions	0.98	3	0.33	0.41	0.747	0.003
	Anger	3.77	3	1.26	1.83	0.141	0.011
	Threat to Freedom	0.24	3	0.08	0.41	0.747	0.008
Residuals	Negative Cognitions	385.35	484	0.80			
	Anger	332.54	484	0.69			
	Threat to Freedom	96.34	484	0.20			

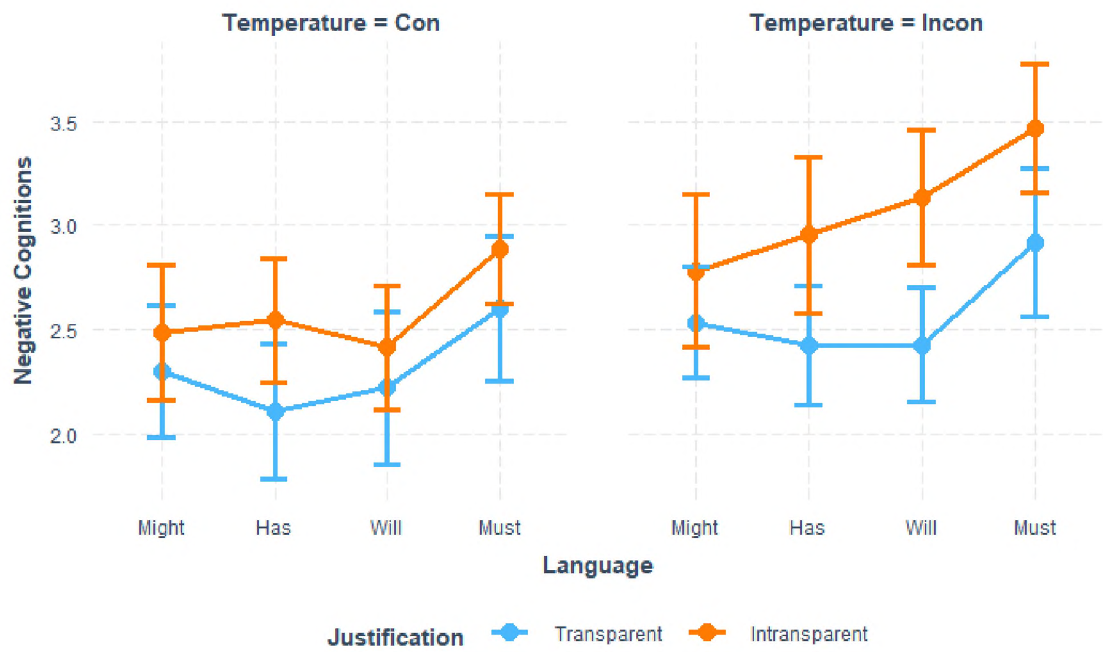

Figure 3.5: Interaction Plots for Language, Temperature, and Justification for Negative Cognitions

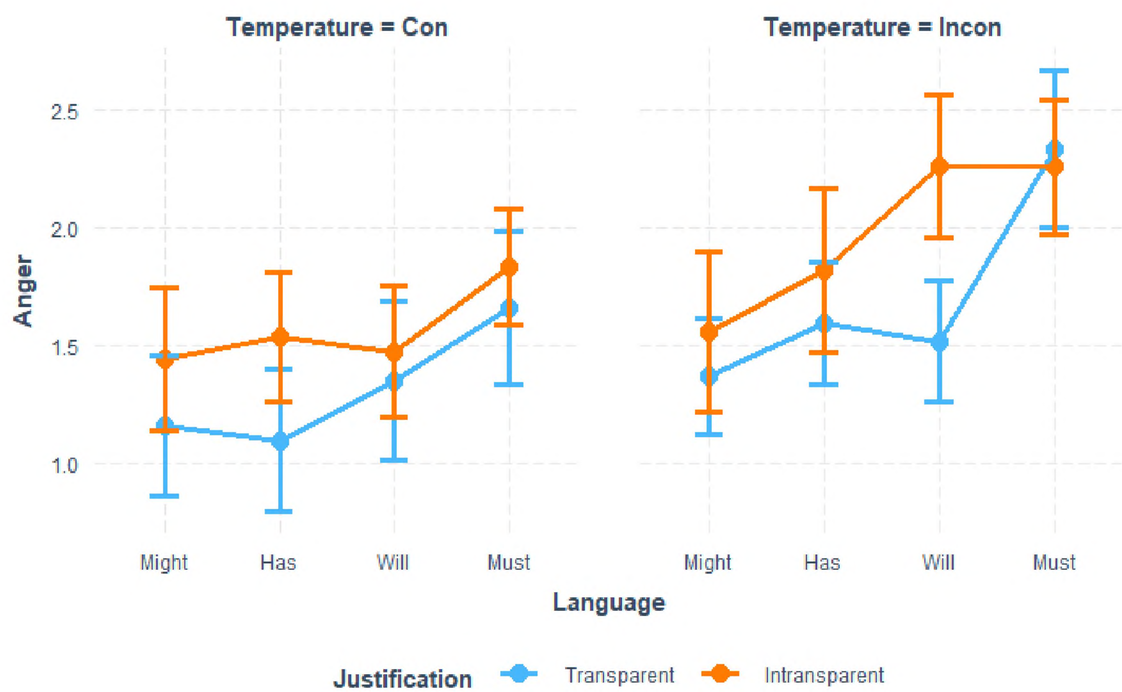

Figure 3.6: Interaction Plots for Language, Temperature, and Justification for Anger

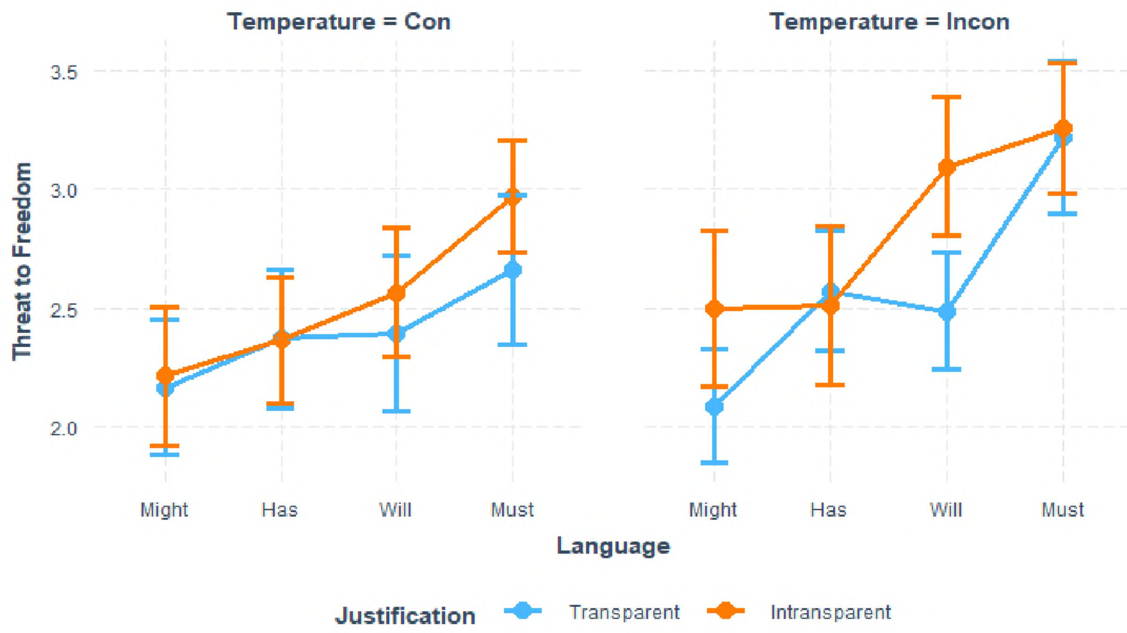

Figure 3.7: Interaction Plots for Language, Temperature, and Justification for Threat to Freedom

However, participants differed in how extreme they may have perceived the change based on their condition in the first message notification. The results suggest that all participants experienced a similar level of reactance, regardless of whether they were in the incongruent or congruent temperature group for the first message notification. Since the Language and Justification assignments remained constant for each participant, they still each had a main effect on reactance for Message notification 2. Participants exposed to more authoritative language and those given incongruent temperatures reported experiencing more reactance, mirroring the results from the first message notification.

To further investigate the effect of initial condition assignment on reactance experienced after Message notification 2, the difference between reactance measured after Message notification 1 and Message notification 2 was taken and another series of

ANOVAs performed with the reactance differences treated as the dependent variables (Table 3.5). Results showed a main effect of Language, Temperature, and Justification on the difference between the reactance measurements after Message notifications 1 and 2. For Language, participants in "Has" and "Will" reported experiencing the greatest difference in reactance with "Might" having the smallest difference and "Must" lying in between, as shown in Figure 3.8. Even though reactance scores were higher for those in the "Must" group after both message notifications compared to the other Language groups, the difference between these scores was lower than "Has" and "Will". This suggests a possible ceiling effect. Regarding Temperature, "Congruent" reported experiencing the greatest difference in reactance compared to "Incongruent" (Figure 3.9). With Temperature being the only manipulation that can potentially change between the first and second message notifications, it appears those who were initially given a congruent temperature had a stronger reaction to the incongruent temperature than those first given an incongruent temperature. As for Justification, the greatest difference for each reactance measure was for participants in the "Intransparent" condition (Figure 3.10). This suggests participants that were given justification for the new temperature felt less reactance than those that were not given justification, even when the temperature strays further away from their stated preferences.

Table 3.4: Main Effects ANOVAs for Message Notification 2

Predictor	Reactance Measure	Sum of Squares	df	Mean Square	F	p	partial $\eta 2$
Language	Negative Cognitions	31.13	3	10.38	10.30	<0.001	0.045
	Anger	42.82	3	14.27	13.96	<0.001	0.067
	Threat to Freedom	51.96	3	17.32	20.02	<0.001	0.096
Temperature	Negative Cognitions	0.08	1	0.08	0.08	0.776	0.003
	Anger	2.12	1	2.12	2.07	0.151	0.009
	Threat to Freedom	2.34	1	2.34	2.70	0.101	0.010
Justification	Negative Cognitions	40.30	1	40.30	39.98	<0.001	0.076
	Anger	20.24	1	20.24	19.79	<0.001	0.039
	Threat to Freedom	14.47	1	14.47	16.73	<0.001	0.033
Language x Temperature	Negative Cognitions	0.58	3	0.19	0.19	0.902	0.001
	Anger	0.92	3	0.31	0.30	0.825	0.001
	Threat to Freedom	1.98	3	0.66	0.76	0.515	0.004
Language x Justification	Negative Cognitions	3.46	3	1.15	1.14	0.331	0.006
	Anger	2.72	3	0.91	0.89	0.448	0.005
	Threat to Freedom	1.21	3	0.40	0.47	0.707	0.003
Temperature x Justification	Negative Cognitions	2.68	1	2.68	2.66	0.103	0.005
	Anger	0.32	1	0.32	0.32	0.574	0.001
	Threat to Freedom	0.61	1	0.61	0.71	0.401	0.001
Language x Temperature x Justification	Negative Cognitions	0.86	3	0.29	0.29	0.836	0.002
	Anger	3.94	3	1.31	1.28	0.279	0.008
	Threat to Freedom	2.71	3	0.90	1.04	0.373	0.006
	Negative Cognitions	487.82	484	1.01			
Residuals	Anger	494.97	484	1.02			
	Threat to Freedom	418.70	484	0.87			

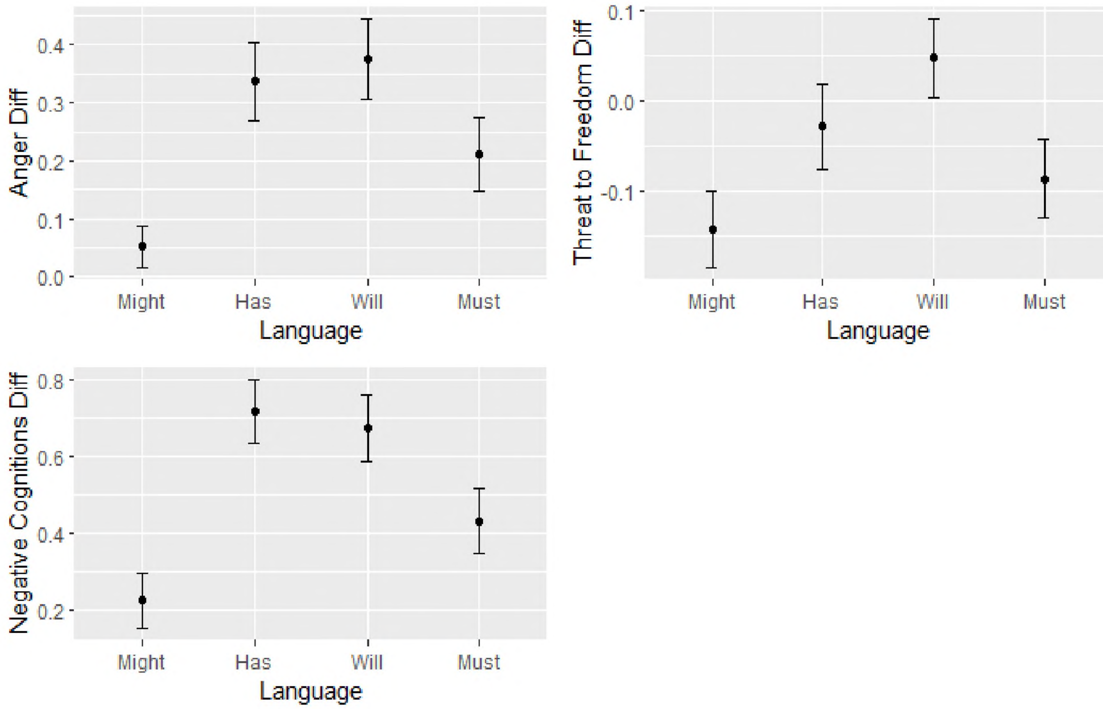

Figure 3.8: Mean and Two Standard Error Scores for the Difference of Reactance Scores Between Message Notifications 1 and 2 by Language Conditions

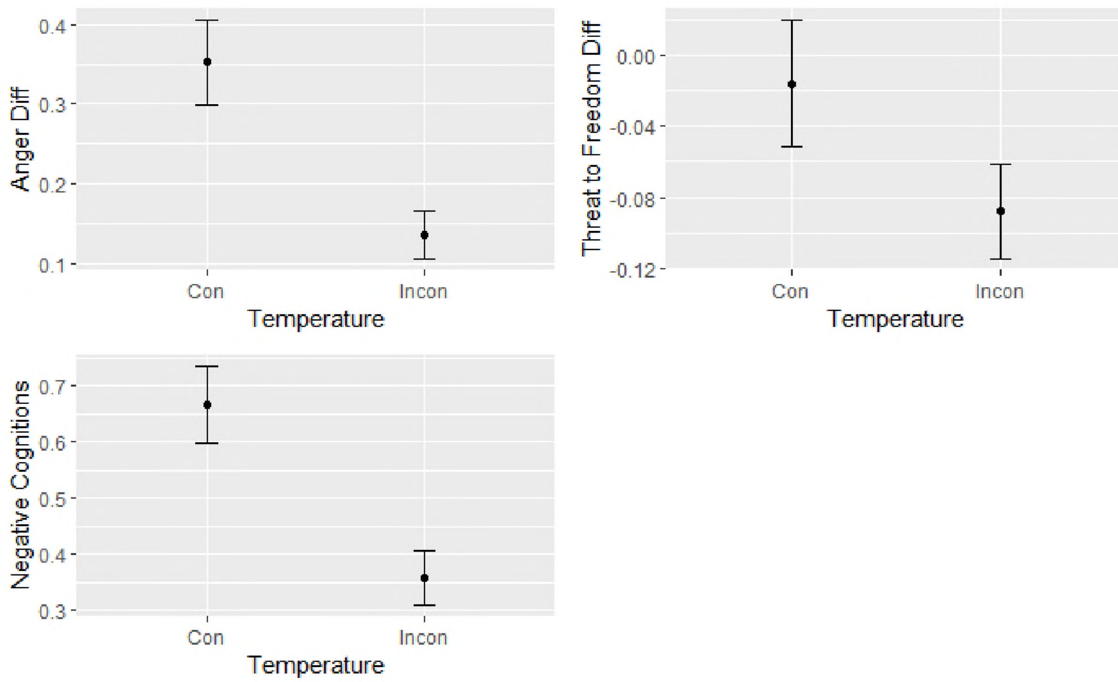

Figure 3.9: Mean and Two Standard Error Scores for the Difference of Reactance Scores Between Message Notifications 1 and 2 by Temperature Conditions

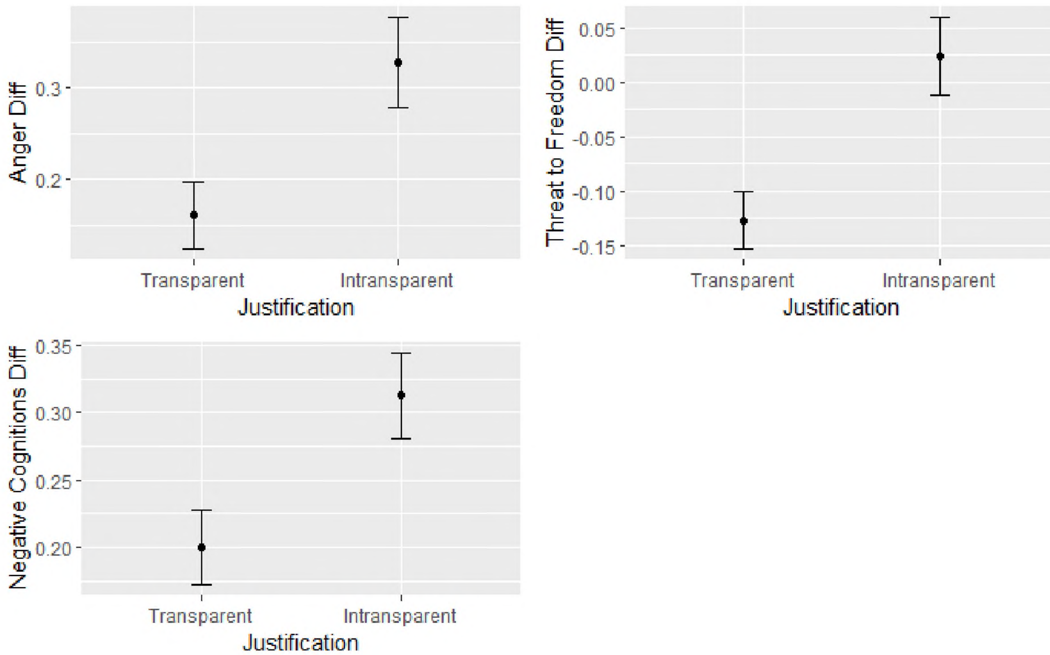

Figure 3.10: Mean and Two Standard Error Scores for the Difference of Reactance Scores Between Message Notifications 1 and 2 by Justification Conditions

Table 3.5: Main Effects ANOVAs for Reactance Measure Differences

Predictor	Reactance Measure	Sum of Squares	df	Mean Square	F	p	partial $\eta 2$
Language	Negative Cognitions	19.75	3	6.58	7.92	< 0.001	0.047
	Anger	7.98	3	2.66	5.99	0.001	0.035
	Threat to Freedom	2.48	3	0.83	3.50	0.016	0.021
Temperature	Negative Cognitions	11.98	1	11.98	14.41	< 0.001	0.024
	Anger	5.98	1	5.98	13.47	< 0.001	0.023
	Threat to Freedom	0.71	1	0.71	3.01	0.083	0.003
Justification	Negative Cognitions	3.91	1	3.91	4.70	0.031	0.010
	Anger	2.11	1	2.11	4.75	0.030	0.010
	Threat to Freedom	2.47	1	2.47	10.44	0.001	0.021
Language x Temperature	Negative Cognitions	0.18	3	0.06	0.07	0.975	0.001
	Anger	1.35	3	0.45	1.01	0.386	0.006
	Threat to Freedom	0.23	3	0.08	0.32	0.810	0.004

Table 3.5: Main Effects ANOVAs for Reactance Measure Differences (cont.)

Language x Justification	Negative Cognitions	2.30	3	0.77	0.92	0.430	0.005
	Anger	0.45	3	0.15	0.34	0.797	0.002
	Threat to Freedom	1.73	3	0.58	2.45	0.063	0.015
Temperature x Justification	Negative Cognitions	0.12	1	0.12	0.14	0.706	0.000
	Anger	0.21	1	0.21	0.47	0.494	0.001
	Threat to Freedom	0.02	1	0.02	0.07	0.790	0.000
Language x Temperature x Justification	Negative Cognitions	0.19	3	0.06	0.08	0.972	0.000
	Anger	0.48	3	0.16	0.36	0.784	0.002
	Threat to Freedom	1.05	3	0.35	1.48	0.220	0.009
Residuals	Negative Cognitions	402.50	484	0.83			
	Anger	214.98	484	0.44			
	Threat to Freedom	114.34	484	0.24			

3.2.6. Behavioral Intention. To assess the degree to which each manipulation affected how likely participants were to accept the temperature suggestions by the thermostat, an ANOVA was conducted with the behavioral intention question as the dependent variable and Language, Temperature, and Justification as the independent variables (Table 3.6: ANOVA for Behavioral Intention). The results indicated that Temperature and Justification had a significant effect on the likelihood of the participant choosing to accept the suggestion with Language not having a significant effect. There was also a significant effect of the interaction between Temperature and Justification on behavioral intention (see Figure 3.11). This means that participants who were given a temperature inside their preferences and an explanation for the thermostat's suggestion were more likely to accept the temperature change. Language being insignificant indicates that the degree of controlling language used by the thermostat did not have a significant effect on whether the participant accepted the temperature suggestion. Shown in Table 3.2, behavioral intention was negatively correlated with all three reactance measures as well. This indicates that the more reactance experienced by the participant, the less likely they are to accept the temperature suggestions from the thermostat.

Table 3.6: ANOVA for Behavioral Intention

Predictor	Sum of Squares	df	Mean Square	F	p	partial $\eta 2$
Language	6.15	3	2.05	1.46	0.226	0.008
Temperature	29.30	1	29.30	20.80	0.000	0.049
Justification	12.44	1	12.44	8.83	0.003	0.018
Language x Temperature	0.81	3	0.27	0.19	0.902	0.000
Language x Justification	3.74	3	1.25	0.89	0.448	0.005
Temperature x Justification	9.91	1	9.91	7.04	0.008	0.014
Language x Temperature x Justification	4.24	3	1.41	1.00	0.392	0.006
Residuals	681.81	484	1.41			

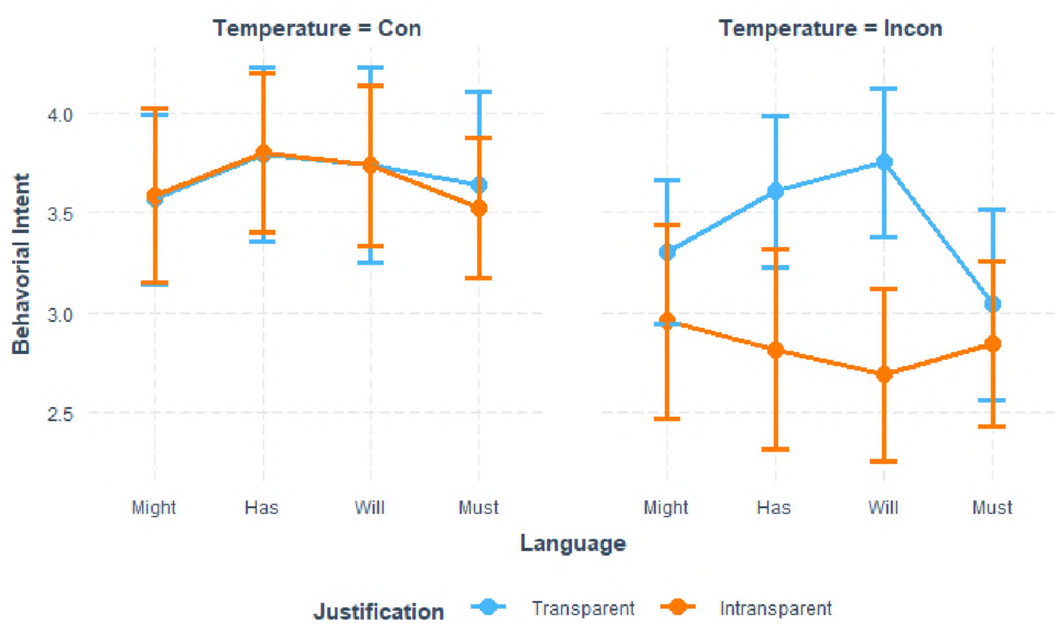

Figure 3.11: Interaction Plot for Language, Temperature, and Justification for the Behavioral Intention Measure with 95% CI Error Bars

3.2.7. Preference Importance. In the beginning of the survey, participants were asked how important their temperature preferences were to them. Table 3.2 shows a positive correlation between how strongly participants felt about their temperature preferences and the anger experienced because of the thermostat's suggestions. ANCOVA's were performed with each reactance measure as the dependent variables, the experimental conditions as the main effects, and how strongly the participants felt about their temperature preferences as a covariate (see Appendix B, Table B.4). The results indicated Preference Importance had a significant effect on Anger ($F(1,483) = 11.6$, $p < 0.001$). This means that participants who cared more about their preferences reported feeling more anger overall. There was also a negative correlation between preference importance and how likely participants were to change their temperature to what the thermostat suggested, indicating that participants who felt strongly about their preferences were less likely to accept the new temperature suggestions.

4. DISCUSSION

A smart home energy management system could reduce residential electricity usage, but compliance may be low for systems that induce reactance in users. This series of two studies examines three aspects of a smart thermostat that may induce reactance, (1) the degree of authoritative language used by the system in its suggestions (Study 1 and 2), (2) the congruence between the thermostat's temperature suggestion and the user's preferences (Study 1 and 2), and (3) whether the thermostat provided Justification for its suggestions (Study 2 only). In Study 1, language and temperature congruence were experimentally manipulated but there were no consistent significant effects on reactance. In Study 2, the presence of a justification was experimentally manipulated as well, which induced reactance. In addition, a second message notification with a greater temperature incongruence was given in Study 2, which showed possible ceiling and floor effects for reactance induction. Overall, these results suggest that if the system needs to adjust the temperature outside of user preferences, providing them with an explanation could reduce user frustration and increase compliance.

Reactance varied due to the (1) language, (2) temperature congruence, and (3) justification. In Study 1, there was no significant effect found from the manipulation of authoritative language. In Study 2, the "should" language condition was replaced with "must" to test a more authoritative language condition. The results of Study 2 suggest that participants feel more reactance when more authoritative language is used. Participants who were told the temperature "must" be changed reported experiencing significantly more reactance than those who received more mild language (i.e., Might, Will, Has). In the second measurement in Study 2, there was little change in the "must" condition, suggesting that there is a ceiling effect on reactance. This finding is consistent with other reactance literature (Brehm, 1966; Hong & Page, 1989; Merz, 1983; Miller et al., 2007; Reynolds-Tylus et al., 2019). In the context of a smart home energy management system, less authoritative language may decrease reactance. However, using more controlling language did not alter the participants' willingness to accept the thermostat's suggestion. This suggests that more authoritative language can increase the likelihood of negative thoughts and feelings toward the thermostat, but not necessarily result in the user disregarding the thermostat's suggestions.

Deviating from temperature preferences (i.e., congruence) also tended to increase feelings of reactance. In Study 1, an effect of temperature was found on negative cognitions, suggesting the manipulation of temperature may have resulted in the formation of negative thoughts. In Study 2, temperature was also shown to be significant in inducing reactance. Participants who were not given a temperature suggestion within their preference reported experiencing more reactance. This congruence also had a significant effect on whether participants accepted the temperature change. They were more likely to accept the change if it was within their temperature preferences. For the second message notification in Study 2, "Congruent" showed a greater difference in reactance. This may be a consequence of subverting the participant's expectations of how the thermostat works. Temperature is also the only manipulation changed between the message notifications, so for those originally in "Congruent", the second message notification presented the biggest difference across each experimental group. With a smart home energy management system, controlling the energy spent on air conditioning is a vital part of the system. When determining what temperatures to use in a residential setting, it is important to stay within the boundaries set by the user, otherwise, consumers may potentially develop distaste for the system and override its suggestions, making the system less effective overall. This potential harm is further shown by the negative correlation between how strongly users feel about their preferences and how likely they are to change the temperature to what the thermostat suggests.

Whether the thermostat provided an explanation for its suggestions was also shown to have a significant effect on reactance. Participants that were not given justification for the new temperature reported experiencing more reactance than those that were given justification. Justification was also shown to have a significant effect on whether users accept the new temperature change. This indicates that giving users an explanation for the new temperature may decrease negative sentiments toward the system and increase the chance that they will accept the suggestions of the thermostat. For the second measurement in Study 2, "Transparent" had a smaller difference in reactance. An explanation being provided to the user may be enough so even when given a temperature further away from their preferences, they will not feel as much reactance. When designing a smart home energy management system, increasing the transparency for the user of why the system is making certain changes and decisions throughout the day may increase user satisfaction.

The two primary limitations to these findings include (1) challenges interpreting differences between Study 1 and 2 and (2) limited ecological validity. To reduce opportunities for participants to relieve feelings of reactance, the negative cognitions thought-listing exercise was removed in Study 2. In addition, anthropomorphism was introduced in Study 2 to increase the saliency of the smart thermostat as an agent they were interacting with. Consequently, it is not appropriate to directly compare the reactance measures in Study 1 and 2. Future work should further explore the effect of these changes. Second, both studies were conducted online and have limited ecological validity. Given the theoretical context, participants may have been more willing to accept temperatures since there were no changes to their physical comfort. Alternatively, participants may not perceive small temperature changes and experience less reactance in a real-world scenario.

Future studies should explore the effect of anthropomorphism and repeated exposure to the smart thermostat on inducing reactance and subsequent behavioral compliance. Manipulating anthropomorphic features of a smart home energy management system could provide interesting insight into how best to design an AI interface for such a system. A repeated measures study could also be conducted to see how users' perception of the system varies as it makes multiple adjustments throughout its operations over time. Due to the simulated nature of this study, the best way to increase the ecological validity of this study would be conduct a field trial with a smart thermostat featuring the aspects explored in this study. By creating a scenario where users directly interact with the thermostat and feel the effects of its operations, the effect of these thermostat features on reactance and behavioral intention can be more accurately determined, and thus contribute even more to the design and development of smart home energy management systems.

APPENDIX A.

STUDY 1 – ADDITIONAL ANALYSES AND ANOVA TABLES

Table A.1: Combined ANCOVA Results

Predictor	Reactance Measure	Sum of Squares	df	Mean Square	F	p	partial $\eta 2$
Language	Negative Cognitions (NLP)	0.01	3	0.00	0.88	0.45	0.014
	Negative Cognitions (Likert)	1.11	3	0.37	0.49	0.69	0.004
	Anger	0.52	3	0.17	0.41	0.74	0.009
	Threat to Freedom	2.20	3	0.73	1.68	0.17	0.019
Temperature	Negative Cognitions (NLP)	0.01	1	0.01	3.88	0.05	0.016
	Negative Cognitions (Likert)	3.57	1	3.57	4.77	0.03	0.014
	Anger	1.61	1	1.61	3.84	0.05	0.011
	Threat to Freedom	0.47	1	0.47	1.08	0.30	0.002
Language x Temperature	Negative Cognitions (NLP)	0.00	3	0.00	0.31	0.82	0.004
	Negative Cognitions (Likert)	1.46	3	0.49	0.65	0.58	0.008
	Anger	1.82	3	0.61	1.44	0.23	0.018
	Threat to Freedom	2.61	3	0.87	1.98	0.12	0.024
Age	Negative Cognitions (NLP)	0.00	1	0.00	0.12	0.73	0.001
	Negative Cognitions (Likert)	1.57	1	1.57	2.10	0.15	0.008
	Anger	2.19	1	2.19	5.22	0.02	0.019
	Threat to Freedom	3.44	1	3.44	7.86	0.01	0.028
Education	Negative Cognitions (NLP)	0.01	1	0.01	3.80	0.05	0.016
	Negative Cognitions (Likert)	2.63	1	2.63	3.52	0.06	0.014
	Anger	1.45	1	1.45	3.47	0.06	0.018
	Threat to Freedom	3.30	1	3.30	7.53	0.01	0.036
Gender	Negative Cognitions (NLP)	0.00	1	0.00	0.16	0.69	0.001
	Negative Cognitions (Likert)	3.54	1	3.54	4.73	0.03	0.020
	Anger	0.14	1	0.14	0.32	0.57	0.001
	Threat to Freedom	0.35	1	0.35	0.80	0.37	0.003
Trait Reactance	Negative Cognitions (NLP)	0.00	1	0.00	0.15	0.70	0.001
	Negative Cognitions (Likert)	11.64	1	11.64	15.56	0.00	0.059
	Anger	9.48	1	9.48	22.61	0.00	0.087
	Threat to Freedom	9.79	1	9.79	22.34	0.00	0.093

Table A.1: Combined ANCOVA Results (cont.)

Mode	Negative Cognitions (NLP)	0.00	1	0.00	0.10	0.76	0.001
	Negative Cognitions (Likert)	0.84	1	0.84	1.12	0.29	0.006
	Anger	3.69	1	3.69	8.80	0.00	0.038
	Threat to Freedom	2.32	1	2.32	5.28	0.02	0.021
Residuals	Negative Cognitions (NLP)	0.47	237	0.00			
	Negative Cognitions (Likert)	177.24	237	0.75			
	Anger	99.38	237	0.42			
	Threat to Freedom	103.84	237	0.44			

Table A.2: ANOVA with Log Transformed Reactance Measures

Predictor	Reactance Measure	Sum of Squares	df	Mean Square	F	p	partial $\eta 2$
Language	Negative Cognitions (NLP)	0.00	3	0.00	0.92	0.43	0.013
	Anger	0.14	3	0.05	0.34	0.79	0.005
Temperature	Negative Cognitions (NLP)	0.01	1	0.01	3.91	0.05	0.016
	Anger	0.45	1	0.45	3.23	0.07	0.013
Language x Temperature	Negative Cognitions (NLP)	0.00	3	0.00	0.21	0.89	0.003
	Anger	0.52	3	0.17	1.24	0.30	0.015
Residuals	Negative Cognitions (NLP)	0.41	242	0.00			
	Anger	33.53	242	0.14			

Table A.3: Quantile Regression for Anger

Predictor	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	1.25	0.08	16.32	0.00
Language: Has	-0.25	0.10	-2.40	0.02
Language: Will	-0.25	0.10	-2.46	0.01
Language: Should	-0.25	0.11	-2.31	0.02
Temperature: Incon	-0.25	0.10	-2.43	0.02
Language: Has x Temperature: Incon	0.25	0.20	1.28	0.20
Language: Will x Temperature: Incon	0.50	0.27	1.87	0.06
Language: Should x Temperature: Incon	0.50	0.19	2.64	0.01

Table A.4: Logistic Regression for Binary Anger Score

Predictor	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	0.50	0.10	5.24	0.00
Language: Has	-0.08	0.13	-0.58	0.56
Language: Will	-0.04	0.13	-0.32	0.75
Language: Should	-0.07	0.13	-0.53	0.60
Temperature: Incon	-0.07	0.13	-0.56	0.58
Language: Has x Temperature: Incon	0.10	0.18	0.53	0.60
Language: Will x Temperature: Incon	0.19	0.18	1.04	0.30
Language: Should x Temperature: Incon	0.14	0.18	0.79	0.43

Table A.5: Combined ANOVA Table for Lower 50% of Trait Reactance Scores

Predictor	Reactance Measure	Sum of Squares	df	Mean Square	F	p	partial $\eta 2$
Language	Negative Cognitions (NLP)	0.01	3	0.00	0.92	0.43	0.024
	Negative Cognitions (Likert)	0.87	3	0.29	0.38	0.77	0.007
	Anger	0.71	3	0.24	0.95	0.42	0.023
	Threat to Freedom	1.01	3	0.34	1.37	0.25	0.031
Temperature	Negative Cognitions (NLP)	0.01	1	0.01	3.45	0.07	0.029
	Negative Cognitions (Likert)	2.25	1	2.25	2.96	0.09	0.025
	Anger	0.44	1	0.44	1.77	0.19	0.015
	Threat to Freedom	0.36	1	0.36	1.49	0.22	0.013
Language x Temperature	Negative Cognitions (NLP)	0.00	3	0.00	0.45	0.71	0.012
	Negative Cognitions (Likert)	3.05	3	1.02	1.33	0.27	0.033
	Anger	0.95	3	0.32	1.26	0.29	0.031
	Threat to Freedom	2.08	3	0.69	2.83	0.04	0.068
Residuals	Negative Cognitions (NLP)	0.29	117	0.00			
	Negative Cognitions (Likert)	89.00	117	0.76			
	Anger	29.42	117	0.25			
	Threat to Freedom	28.61	117	0.24			

Table A.6: Study 1 ANOVA Table for Upper 50% of Trait Reactance Scores

Predictor	Reactance Measure	Sum of Squares	df	Mean Square	F	p	partial $\eta 2$
Language	Negative Cognitions (NLP)	0.00	3	0.00	0.24	0.87	0.006
	Negative Cognitions (Likert)	1.75	3	0.58	0.71	0.55	0.018
	Anger	1.37	3	0.46	0.95	0.42	0.022
	Threat to Freedom	0.09	3	0.03	0.11	0.95	0.003
Temperature	Negative Cognitions (NLP)	0.00	1	0.00	0.57	0.45	0.005
	Negative Cognitions (Likert)	1.22	1	1.22	1.49	0.23	0.013
	Anger	0.61	1	0.61	1.25	0.26	0.011
	Threat to Freedom	0.03	1	0.03	0.10	0.75	0.001
Language x Temperature	Negative Cognitions (NLP)	0.01	3	0.00	1.38	0.25	0.034
	Negative Cognitions (Likert)	3.89	3	1.30	1.57	0.20	0.039
	Anger	2.59	3	0.86	1.79	0.15	0.044
	Threat to Freedom	1.64	3	0.55	2.00	0.12	0.049
Residuals	Negative Cognitions (NLP)	0.17	117	0.00			
	Negative Cognitions (Likert)	96.39	117	0.82			
	Anger	56.48	117	0.48			
	Threat to Freedom	31.98	117	0.27			

APPENDIX B.

STUDY 2 – ADDITIONAL ANALYSES AND ANOVA TABLE

Table B.1: ANCOVA for Message Notification 1

Predictor	Reactance Measure	Sum of Squares	df	Mean Square	F	p	partial $\eta 2$
Language	Negative Cognitions	21.21	3	7.07	9.06	0.00	0.045
	Anger	27.99	3	9.33	15.74	0.00	0.080
	Threat to Freedom	44.48	3	14.83	27.19	0.00	0.132
Temperature	Negative Cognitions	14.04	1	14.04	18.00	0.00	0.044
	Anger	15.22	1	15.22	25.69	0.00	0.052
	Threat to Freedom	5.63	1	5.63	10.33	0.00	0.020
Justification	Negative Cognitions	19.11	1	19.11	24.50	0.00	0.044
	Anger	9.28	1	9.28	15.66	0.00	0.024
	Threat to Freedom	4.99	1	4.99	9.15	0.00	0.014
Language x Temperature	Negative Cognitions	0.86	3	0.29	0.37	0.78	0.002
	Anger	2.36	3	0.79	1.33	0.27	0.008
	Threat to Freedom	1.60	3	0.53	0.98	0.40	0.006
Language x Justification	Negative Cognitions	1.60	3	0.53	0.68	0.56	0.004
	Anger	1.17	3	0.39	0.66	0.58	0.004
	Threat to Freedom	1.91	3	0.64	1.17	0.32	0.007
Temperature x Justification	Negative Cognitions	1.47	1	1.47	1.88	0.17	0.004
	Anger	0.00	1	0.00	0.00	0.97	0.000
	Threat to Freedom	0.23	1	0.23	0.42	0.52	0.001
Language x Temperature x Justification	Negative Cognitions	1.07	3	0.36	0.46	0.71	0.003
	Anger	3.33	3	1.11	1.87	0.13	0.012
	Threat to Freedom	1.19	3	0.40	0.72	0.54	0.005
Age	Negative Cognitions	1.93	1	1.93	2.48	0.12	0.005
	Anger	10.59	1	10.59	17.87	0.00	0.028
	Threat to Freedom	2.78	1	2.78	5.10	0.02	0.005
Education	Negative Cognitions	0.28	1	0.28	0.36	0.55	0.001
	Anger	1.19	1	1.19	2.01	0.16	0.002
	Threat to Freedom	5.96	1	5.96	10.92	0.00	0.018

Table B.1: ANCOVA for Message Notification 1 (cont.)

Gender	Negative Cognitions	0.01	1	0.01	0.01	0.92	0.000
	Anger	0.22	1	0.22	0.36	0.55	0.000
	Threat to Freedom	0.73	1	0.73	1.34	0.25	0.001
Trait Reactance	Negative Cognitions	7.83	1	7.83	10.04	0.00	0.018
	Anger	34.64	1	34.64	58.44	0.00	0.096
	Threat to Freedom	34.13	1	34.13	62.58	0.00	0.098
Mode	Negative Cognitions	1.43	1	1.43	1.83	0.18	0.002
	Anger	3.91	1	3.91	6.59	0.01	0.010
	Threat to Freedom	5.84	1	5.84	10.70	0.00	0.018
Residuals	Negative Cognitions	373.70	479	0.78			
	Anger	283.91	479	0.59			
	Threat to Freedom	261.20	479	0.55			

Table B.2: ANCOVA for Message Notification 2

Predictor	Reactance Measure	Sum of Squares	df	Mean Square	F	p	partial $\eta 2$
Language	Negative Cognitions	31.13	3	10.38	11.01	0.00	0.053
	Anger	42.82	3	14.27	17.41	0.00	0.084
	Threat to Freedom	51.96	3	17.32	24.01	0.00	0.111
Temperature	Negative Cognitions	0.08	1	0.08	0.09	0.77	0.002
	Anger	2.12	1	2.12	2.58	0.11	0.007
	Threat to Freedom	2.34	1	2.34	3.24	0.07	0.008
Justification	Negative Cognitions	40.30	1	40.30	42.76	0.00	0.070
	Anger	20.24	1	20.24	24.69	0.00	0.035
	Threat to Freedom	14.47	1	14.47	20.06	0.00	0.032
Language x Temperature	Negative Cognitions	1.48	3	0.49	0.52	0.67	0.003
	Anger	1.32	3	0.44	0.54	0.66	0.003
	Threat to Freedom	1.66	3	0.55	0.77	0.51	0.004
Language x Justification	Negative Cognitions	2.91	3	0.97	1.03	0.38	0.006
	Anger	1.06	3	0.35	0.43	0.73	0.003
	Threat to Freedom	0.08	3	0.03	0.04	0.99	0.000
Temperature x Justification	Negative Cognitions	2.31	1	2.31	2.45	0.12	0.005
	Anger	0.08	1	0.08	0.09	0.76	0.000
	Threat to Freedom	0.30	1	0.30	0.42	0.52	0.001
Language x Temperature x Justification	Negative Cognitions	0.85	3	0.28	0.30	0.82	0.002
	Anger	2.72	3	0.91	1.10	0.35	0.007
	Threat to Freedom	1.58	3	0.53	0.73	0.53	0.005
Age	Negative Cognitions	18.21	1	18.21	19.33	0.00	0.036
	Anger	27.80	1	27.80	33.92	0.00	0.050
	Threat to Freedom	7.07	1	7.07	9.80	0.00	0.011
Education	Negative Cognitions	0.14	1	0.14	0.15	0.70	0.000
	Anger	2.65	1	2.65	3.23	0.07	0.005
	Threat to Freedom	7.14	1	7.14	9.89	0.00	0.015

Table B.2: ANCOVA For Message Notification 2 (cont.)

Gender	Negative Cognitions	0.02	1	0.02	0.02	0.90	0.000
	Anger	0.19	1	0.19	0.23	0.63	0.000
	Threat to Freedom	0.12	1	0.12	0.16	0.69	0.002
Trait Reactance	Negative Cognitions	14.76	1	14.76	15.66	0.00	0.027
	Anger	59.44	1	59.44	72.52	0.00	0.113
	Threat to Freedom	53.02	1	53.02	73.49	0.00	0.116
Mode	Negative Cognitions	3.33	1	3.33	3.54	0.06	0.004
	Anger	15.00	1	15.00	18.29	0.00	0.030
	Threat to Freedom	8.64	1	8.64	11.97	0.00	0.021
Residuals	Negative Cognitions	451.40	479	0.94			
	Anger	392.62	479	0.82			
	Threat to Freedom	345.60	479	0.72			

Table B.3: ANCOVA for Reactance Measure Differences

Predictor	Reactance Measure	Sum of Squares	df	Mean Square	F	p	partial $\eta 2$
Language	Negative Cognitions	19.75	3	6.58	8.02	0.00	0.052
	Anger	7.98	3	2.66	6.25	0.00	0.040
	Threat to Freedom	2.48	3	0.83	3.61	0.01	0.020
Temperature	Negative Cognitions	11.98	1	11.98	14.61	0.00	0.026
	Anger	5.98	1	5.98	14.07	0.00	0.026
	Threat to Freedom	0.71	1	0.71	3.11	0.08	0.003
Justification	Negative Cognitions	3.91	1	3.91	4.76	0.03	0.007
	Anger	2.11	1	2.11	4.96	0.03	0.007
	Threat to Freedom	2.47	1	2.47	10.77	0.00	0.019
Language x Temperature	Negative Cognitions	0.37	3	0.12	0.15	0.93	0.001
	Anger	1.17	3	0.39	0.92	0.43	0.005
	Threat to Freedom	0.09	3	0.03	0.13	0.94	0.002
Language x Justification	Negative Cognitions	1.85	3	0.62	0.75	0.52	0.005
	Anger	0.74	3	0.25	0.58	0.63	0.004
	Threat to Freedom	1.77	3	0.59	2.58	0.05	0.016
Temperature x Justification	Negative Cognitions	0.10	1	0.10	0.12	0.73	0.000
	Anger	0.10	1	0.10	0.22	0.64	0.000
	Threat to Freedom	0.01	1	0.01	0.02	0.88	0.000
Language x Temperature x Justification	Negative Cognitions	0.13	3	0.04	0.05	0.98	0.000
	Anger	0.41	3	0.14	0.32	0.81	0.002
	Threat to Freedom	1.05	3	0.35	1.53	0.20	0.010
Age	Negative Cognitions	8.28	1	8.28	10.09	0.00	0.019
	Anger	4.08	1	4.08	9.58	0.00	0.014
	Threat to Freedom	0.98	1	0.98	4.30	0.04	0.005
Education	Negative Cognitions	0.03	1	0.03	0.03	0.86	0.000
	Anger	0.29	1	0.29	0.67	0.41	0.002
	Threat to Freedom	0.05	1	0.05	0.23	0.63	0.000

Table B.3: ANCOVA for Reactance Measure Differences (cont.)

Gender	Negative Cognitions	0.05	1	0.05	0.06	0.81	0.000
	Anger	0.00	1	0.00	0.00	0.96	0.000
	Threat to Freedom	1.44	1	1.44	6.27	0.01	0.014
Trait Reactance	Negative Cognitions	1.09	1	1.09	1.33	0.25	0.002
	Anger	3.33	1	3.33	7.83	0.01	0.012
	Threat to Freedom	2.07	1	2.07	9.06	0.00	0.018
Mode	Negative Cognitions	0.40	1	0.40	0.49	0.49	0.000
	Anger	3.59	1	3.59	8.45	0.00	0.015
	Threat to Freedom	0.27	1	0.27	1.20	0.27	0.002
Residuals	Negative Cognitions	393.00	479	0.82			
	Anger	203.76	479	0.43			
	Threat to Freedom	109.63	479	0.23			

Table B.4: Combined ANCOVA with Participant Temperature Preference Importance as Covariate

Predictor	Reactance Measure	Sum of Squares	df	Mean Square	F	p	partial $\eta 2$
Language	Negative Cognitions	21.21	3	7.07	8.87	0.00	0.043
	Anger	27.99	3	9.33	13.88	0.00	0.073
	Threat to Freedom	44.48	3	14.83	23.38	0.00	0.118
Temperature	Negative Cognitions	14.04	1	14.04	17.61	0.00	0.047
	Anger	15.22	1	15.22	22.64	0.00	0.055
	Threat to Freedom	5.63	1	5.63	8.88	0.00	0.022
Justification	Negative Cognitions	19.11	1	19.11	23.97	0.00	0.047
	Anger	9.28	1	9.28	13.80	0.00	0.022
	Threat to Freedom	4.99	1	4.99	7.87	0.01	0.014
Language x Temperature	Negative Cognitions	0.74	3	0.25	0.31	0.82	0.002
	Anger	2.69	3	0.90	1.34	0.26	0.008
	Threat to Freedom	1.88	3	0.63	0.99	0.40	0.006
Language x Justification	Negative Cognitions	1.48	3	0.49	0.62	0.60	0.004
	Anger	2.29	3	0.76	1.13	0.33	0.007
	Threat to Freedom	3.17	3	1.06	1.66	0.17	0.010
Temperature x Justification	Negative Cognitions	1.71	1	1.71	2.15	0.14	0.004
	Anger	0.00	1	0.00	0.00	0.99	0.000
	Threat to Freedom	0.37	1	0.37	0.58	0.45	0.001
Language x Temperature x Justification	Negative Cognitions	0.97	3	0.32	0.41	0.75	0.003
	Anger	3.69	3	1.23	1.83	0.14	0.011
	Threat to Freedom	2.48	3	0.83	1.30	0.27	0.008
Preference Importance	Negative Cognitions	0.13	1	0.13	0.17	0.68	0.001
	Anger	7.82	1	7.82	11.63	0.00	0.023
	Threat to Freedom	1.35	1	1.35	2.13	0.14	0.005
Residuals	Negative Cognitions	385.16	483	0.80			
	Anger	324.81	483	0.67			
	Threat to Freedom	306.31	483	0.63			

BIBLIOGRAPHY

Air conditioning accounts for about 12% of U.S. home energy expenditures - Today in Energy - U.S. Energy Information Administration (EIA). (n.d.). Retrieved May 20, 2021, from https://www.eia.gov/todayinenergy/detail.php?id=36692

Batchu, R., & Pindoriya, N. M. (2015). Residential demand response algorithms: State-of-the-art, key issues and challenges. *Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST*, *154*(2), 18–32. https://doi.org/10.1007/978-3-319-25479-1_2

Brehm, J. W. (1966). *A Theory of Psychological Reactance*. Academic Press.

Brehm, J. W. (1989). Psychological Reactance: Theory and Applications. *Advances in Consumer Research*, *16*(1), 72–75. https://doi.org/10.1007/BF00290976

Causes | Facts – Climate Change: Vital Signs of the Planet. (n.d.). Retrieved June 3, 2021, from https://climate.nasa.gov/causes/

Climate Impacts on Energy | Climate Change Impacts | US EPA. (n.d.). Retrieved June 3, 2021, from https://19january2017snapshot.epa.gov/climate-impacts/climate-impacts-energy_.html

Delmas, M. A., Fischlein, M., & Asensio, O. I. (2013). Information strategies and energy conservation behavior: A meta-analysis of experimental studies from 1975 to 2012. *Energy Policy*, *61*, 729–739. https://doi.org/10.1016/j.enpol.2013.05.109

Demand Response | Department of Energy. (n.d.). Retrieved May 19, 2021, from https://www.energy.gov/oe/activities/technology-development/grid-modernization-and-smart-grid/demand-response

Dillard, J. P., Kim, J., & Li, S. S. (2018). Anti-Sugar-Sweetened Beverage Messages Elicit Reactance: Effects on Attitudes and Policy Preferences. *Journal of Health Communication*, *23*(8), 703–711. https://doi.org/10.1080/10810730.2018.1511012

Dillard, J. P., & Shen, L. (2005). On the nature of reactance and its role in persuasive health communication. *Communication Monographs*, *72*(2), 144–168. https://doi.org/10.1080/03637750500111815

Ehrenbrink, P., & Möller, S. (2018). Development of a reactance scale for human–computer interaction. *Quality and User Experience*, *3*(1), 1–13. https://doi.org/10.1007/s41233-018-0016-y

Electric Power Monthly - U.S. Energy Information Administration (EIA). (n.d.). Retrieved May 18, 2021, from https://www.eia.gov/electricity/monthly/

Energy and climate change — European Environment Agency. (n.d.). Retrieved June 3, 2021, from https://www.eea.europa.eu/signals/signals-2017/articles/energy-and-climate-change

Ghazali, A. S., Ham, J., Barakova, E. I., & Markopoulos, P. (2018a). Effects of robot facial characteristics and gender in persuasive human-robot interaction. *Frontiers Robotics AI*, *5*(JUN), 1–16. https://doi.org/10.3389/frobt.2018.00073

Ghazali, A. S., Ham, J., Barakova, E. I., & Markopoulos, P. (2018b). Poker Face Influence: Persuasive Robot with Minimal Social Cues Triggers Less Psychological Reactance. *RO-MAN 2018 - 27th IEEE International Symposium on Robot and Human Interactive Communication*, 940–946. https://doi.org/10.1109/ROMAN.2018.8525535

Global electricity consumption continues to rise faster than population - Today in Energy - U.S. Energy Information Administration (EIA). (n.d.). Retrieved May 20, 2021, from https://www.eia.gov/todayinenergy/detail.php?id=44095

Helia Zandi, Teja Kuruganti, Edward Vineyard, David Fugate. (2017). *Home Energy Management Systems: An Overview*. Unpublished.

Hong, S.-M., & Page, S. (1989). A Psychological Reactance Scale: Development, Factor Structure and Reliability. *Psychological Reports*, *64*(3), 1323–1326.

Knight, R. L., Lutzenhiser, L., & Lutzenhiser, S. (2006). Why Comprehensive Residential Energy Efficiency Retrofits Are Undervalued. *ACEEE Summer Session 2006*, 1–10.

Merz, J. (1983). Fragbogen zur Messung der psychologischen Reaktanz [A questionnaire for the measurement of psychological reactance]. *Diagnostica*, *29*(1), 75–82.

Miller, C. H., Lane, L. T., Deatrick, L. M., Young, A. M., & Potts, K. A. (2007). Psychological reactance and promotional health messages: the effects of controlling language, lexical concreteness, and the restoration of freedom. *Human Communication Research*, *33*(2), 219–240.

Peer, E., Brandimarte, L., Samat, S., & Acquisti, A. (2017). Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. *Journal of Experimental Social Psychology*, *70*, 153–163. https://doi.org/10.1016/j.jesp.2017.01.006

Reynolds-Tylus, T. (2019). Psychological Reactance and Persuasive Health Communication: A Review of the Literature. *Frontiers in Communication*, *4*. https://doi.org/10.3389/fcomm.2019.00056

Reynolds-Tylus, T., Martinez Gonzalez, A., & Quick, B. L. (2019). The Role of Choice Clustering and Descriptive Norms in Attenuating Psychological Reactance to Water and Energy Conservation Messages. *Environmental Communication*, *13*(7), 847–863. https://doi.org/10.1080/17524032.2018.1461672

Roubroeks, M. A. J., Ham, J. R. C., & Midden, C. J. H. (2010). The dominant robot: Threatening robots cause psychological reactance, especially when they have incongruent goals. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *6137 LNCS*, 174–184. https://doi.org/10.1007/978-3-642-13226-1_18

Thiruvengada, H., Dharwada, P., Tharanathan, A., Foslien, W., Putrevu, S., & Beane, J. (2011). Balancing trust and automation needs for effective home energy management. *Communications in Computer and Information Science*, *173 CCIS*(PART 1), 86–90. https://doi.org/10.1007/978-3-642-22098-2_18

Yang, H., Lee, W., & Lee, H. (2018). IoT Smart Home Adoption: The Importance of Proper Level Automation. *Journal of Sensors*, *2018*. https://doi.org/10.1155/2018/6464036

Yassine, A. (2016). Implementation challenges of automatic demand response for households in smart grids. *2016 3rd International Conference on Renewable Energies for Developing Countries, REDEC 2016*. https://doi.org/10.1109/REDEC.2016.7577546

Zipperer, A., Aloise-Young, P. A., Suryanarayanan, S., Roche, R., Earle, L., Christensen, D., Bauleo, P., & Zimmerle, D. (2013). Electric energy management in the smart home: Perspectives on enabling technologies and consumer behavior. *Proceedings of the IEEE*, *101*(11), 2397–2408. https://doi.org/10.1109/JPROC.2013.2270172

VITA

Matthew Heatherly received his Bachelor of Science degree in Nuclear Engineering from Missouri University of Science and Technology in Fall 2018. He enrolled in the master's degree program in Engineering Management at Missouri University of Science and Technology in Fall 2019. He carried out research under Dr. Casey Canfield starting in March 2020, later joined by Dr. Denise Baker in June 2020. He received his Master of Science degree in Engineering Management from Missouri S&T in July 2021.