THESIS

TO SAVE CARBON OR TO SAVE FOREST:

COMPARING EFFECTIVENESS OF CLIMATE IMPACT MESSAGING ON HOUSEHOLD ENERGY BEHAVIOR

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ABSTRACT

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COMPARING EFFECTIVENESS OF CLIMATE IMPACT MESSAGING ON HOUSEHOLD ENERGY BEHAVIOR

Impacts from the climate change crisis are already being seen across the world. With these adverse events, awareness of, and communication about, climate change is increasing. Despite this, though, there has been an inadequate increase in climate action. Thus, it is important to determine the best ways to communicate climate impact information to consumers. The present study investigates how we can best frame climate impact messages for them to be effective in changing consumer behavior. Specifically, the effectiveness of four different carbon messages was examined in the context of household energy behavior.

While meeting U.S. electricity demand with renewable energy is an attainable goal, it will require greater flexibility in the electricity grid, including flexibility in demand timing. Thus far, utility companies have used price signals as a main form of demand response. However, communicating environmental savings to consumers in addition to/instead of price savings is an emerging trend. For these reasons, the present study focused on the impact that climate impact messages may have consumers' willingness to shift their appliance use toward a time of day when renewable energy sources are more plentiful.

Participants were recruited online and through local environmental groups. In an online survey, 244 participants were randomly assigned to one of four messaging conditions for three household appliances (air conditioning, dishwasher, and washing machine). The goal of the

messages is to convince consumers to shift the times they use these appliances, and, as a result, shift demand on the electricity grid, to 9 a.m. (a time with higher renewable energy sources on average in the continental U.S.). Based on previous message framing research, the messages tested were framed in terms of environmental gain: specifically, the environmental savings accomplished by the behavior change. Three messages were created based on U.S. greenhouse gas emissions data, with savings calculated in terms of pounds of CO_2 emissions, percent change in CO_2 emissions, and the equivalent of acres of forest planted. (For example, "…would cut your yearly CO_2 emissions by the equivalent of planting 475 square feet of forest…") A fourth message simply stated that the behavior is "more environmentally friendly" to test a non-numeric message. Participants were asked the likelihood of changing the time that they run each appliance, first with no message present (which acted as a baseline covariate) and then with the randomly assigned message present. Because previous research has shown that numeracy plays a role in the effectiveness of numerical messaging, I also tested a numeracy moderation effect.

To compare participants' likelihood of switching across messaging conditions and to test whether numeracy played a moderating role, I ran individual analyses of covariance (ANCOVA) for each of the three appliances. This allowed me to control for participants' baseline likelihood (i.e., with no environmental message), by adding it as a covariate. Across all three appliances, neither the main effects of messaging condition and numeracy nor the interaction between the two were significant predictors of post-test likelihood. This means there was no evidence to suggest a difference in effectiveness between the messaging conditions, although there was a notable nonsignificant trend of the forest equivalency message performing better. Additionally, I ran mean differences tests comparing baseline likelihood and experimental likelihood for each of the conditions. These tests showed strong evidence that each climate impact message significantly increased participants' likelihood of switching the time they use their appliances

The finding that the messages were effective confirms the need to understand how to optimize the impact that climate impact messages can have on behavior and the mechanisms through which they are effective. Furthermore, the finding that the forest equivalency message had the strongest effect of the four messages (though not statistically significant) is worth researching further, because of the potential applications of this finding. Communicating climate impact information in terms of equivalency in square footage of forest planted easily allows for visualizations to be included, more so than other numerical messages, which may increase a message's saliency and persuasiveness. Furthermore, the findings of the present study and a pilot study that is reported suggest that future research should examine effectiveness within different segments of the population. More research, overall, is needed to further investigate the most effective ways to inform consumers about the climate impact of their behaviors.

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INTRODUCTION

Climate change is a global crisis currently impacting the world. Humans, non-human animals, and nature alike are being adversely affected by warming land temperatures, changing precipitation patterns, and rising sea levels, all of which are occurring at an alarming rate (Arneth et al., 2019). The driver behind these changes is the increased release of greenhouse gases (GHGs) such as carbon dioxide (CO_2), methane, and nitrous oxide into the atmosphere (Hegerl et al., 2007). CO_2 is of particular concern due to its rising concentrations in the atmosphere (Keeling, 1997). Human activities, especially burning fossil fuel for transportation and electricity, cutting down forests for resources, and raising livestock for food, are responsible for much of this increase in GHG emissions (European Commission, n.d.).

This human-caused crisis requires a human-driven solution and individual behavior change is a crucial part of that solution (Liverani, 2009). Individuals are largely aware of and concerned by the climate crisis: in a nationally representative survey conducted by the Yale Program on Climate Change Communication, 64% of Americans surveyed said they were at least "somewhat worried" about global warming (Leiserowitz et al., 2022). While individuals are largely aware of and concerned by the climate crisis, this increase in awareness and concern has not necessarily led to an increase in action. For example, in another survey, 39% of Americans said they would be at least somewhat likely to consider an electric vehicle the next time they purchase a car, but in the first quarter of 2022, electric vehicles sales only made up 4.6% of all car sales in the U.S. (Blanco, 2022; Spencer & Funk, 2021).

This is not all that surprising, given that extensive research confirms that increased knowledge on a subject does not directly cause an individual to take action (Abrahamse et al., 2005; Geller, 1981). Having said that, although information alone does not motivate behavior change, it can facilitate behavior change in an already motivated population. Given that many consumers are already motivated to behave and consume more sustainably, more research is needed on the types of communications that are successful in spurring pro-environmental behavior change (Jain et al., 2020).

Climate Impact Communications

A recent literature review emphasizes that consumers are, on their own, unable to determine which behavior changes are worth making for climate change (Thøgersen, 2021). For example, a study investigating consumer perceptions of energy-saving behaviors found that most consumers misidentified the best behaviors to save energy and largely misestimated the relative energy uses of different behaviors (Attari et al., 2010). The link between consumer behavior and climate change, while significant, is complex and a typical consumer is not able to calculate carbon footprints associated with any given behavior or product they may pursue. Consumers need considerable help choosing impactful pro-environmental behaviors. Product labeling, then, is one method for helping consumers make environmentally friendly purchase decisions.

Product labeling. In the U.S., information labeling for energy-driven products, such as new vehicles or household appliances, dates to the 1970's. For instance, the U.S. Environmental Protection Agency offers fuel economy and environment labels for all new vehicles (see Figure 1), which describe the car's fuel mileage, estimated gasoline costs, a greenhouse gas rating, and a smog rating. For household appliances in the U.S., the Federal Trade Commission requires manufacturers to include EnergyGuide labels (see Figure 1) that offer annual energy usage and cost estimates for that product. Some of these products also carry the EnergyStar label, designating them as energy efficient (Energy Star, n.d.). Similarly, in the European Union (EU), a directive requires appliance manufacturers to include an EU energy efficiency label that utilizes a colored, graded rating system, with ratings from A to G and from green to red (European Commission, 2021).

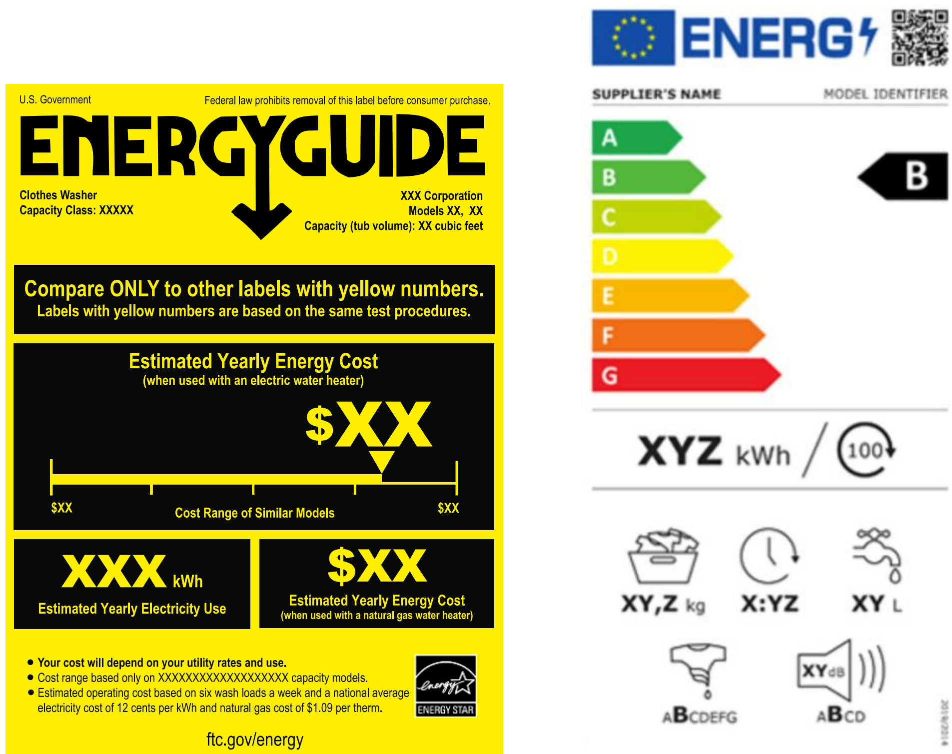

Figure 1. EnergyGuide label for a washing machine (left) and EU energy efficiency label for a washing machine (right) (Federal Trade Commission, 2022; De Ayala & Solà, 2022).

In addition to government agencies, many private companies are informing individual consumers about the environmental cost of different products and behaviors by stating the GHG emissions associated with each. For instance, public-facing carbon footprint labels – labels on products, similar to nutrition labels, that state the amount of CO_2 emissions released in the lifecycle of the product – are becoming increasingly popular (Wolk-Lewanowicz, 2020). As shown in Figure 2, these labels tend to state the carbon footprint in terms of grams of CO_2 emissions. For example, Just Salad provides calorie and carbon information online and in-store on all menu items. Similarly, skincare brand Cocokind dedicates one side of each product's packaging to sustainability facts, including carbon emissions associated with the product.

Figure 2. Examples of carbon footprint labeling: left, Just Salad's chicken fajita bowl; right, Cocokind's chia face oil (Just salad, n.d.; Cocokind, 2021).

Feedback systems. In addition to product labeling, climate impact information associated with energy behavior is sometimes communicated to individuals via feedback systems. In terms of sustainable behaviors, feedback systems have been used most in the context of household energy use. The advent of advanced (or 'smart') metering infrastructure has made it possible to deliver more customized feedback for consumers (Karlin et al., 2015). This energy feedback may be presented directly to consumers (i.e., on a smart meter interface) or indirectly (i.e., on a monthly bill) (Darby, 2001). The main ways of presenting energy use feedback are in kilowatt hours (kWh) or monetary units (see Figure 3), and the main way of presenting environmental impact information in this context is in carbon emissions in kilograms (kg) (Karjalainen, 2011). However, innovative methods of presenting feedback have been explored, such as the Oberlin Environmental Dashboard, which displays educational animations with real-time data on electricity and water consumptions in buildings across Oberlin College's campus and the city at large (Oberlin Environmental Dashboard, 2023).

Figure 3. Consumer-facing 'Energy Dashboard' software application given to UK households, from Wood et al. (2019)

Effectiveness of carbon messaging. Research on product labels with climate impact information like these has shown that consumers across the globe are in support of being presented the information and, furthermore, that the labels can impact consumers' decisions (Groening et al., 2015; Hartikainen et al., 2014; Tan et al., 2014). In the case of EnergyGuide and EnergyStar labels specifically, effectiveness has been mixed. One study (Newell & Siikamäki, 2014) found that the presence of an EnergyStar label significantly impacted participants' household appliance choices, as did the presence of an EU-style energy letter grade, but the presence of the EnergyGuide label did not have a significant impact; other attributes that significantly impacted choices included purchase price, energy operating cost, and CO_2 emissions. Research has also revealed that consumers often do not know how to interpret the information they are given (Rondoni & Grasso, 2021; Li et al., 2017). When researchers in the

U.K., for instance, conducted focus groups to investigate public perceptions of carbon labels on grocery items, participants consistently noted being unable to comprehend the measurements of carbon that were presented to them (grams of CO_2 or CO_2 equivalent) (Upham et al., 2011). Likewise, in a qualitative study on the EU's energy efficiency labels, nearly all the consumers interviewed said they find it difficult to understand the energy usage information on the label (which is presented in kWh) (De Ayala & Solà, 2022).

Overall, feedback on energy usage has been effective in encouraging behavior change (i.e., energy conservation; Darby, 2001; Fischer, 2008; Karlin et al., 2015). One study assessed the effectiveness of twelve different North American pilot programs of in-home displays that provide real-time, direct feedback to homeowners (Faruqui et al., 2010). They found that these pilot programs reduced electricity consumption by an average of 6.5%. Overall, direct feedback systems typically see a savings between 5 – 15%, while indirect feedback systems typically see savings ranging from 0-10% (Darby, 2006). Importantly, however, the main ways of presenting energy use feedback are in kilowatt hours (kWh) or monetary units (see Figure 3), and the main way of presenting environmental impact information in this context is in carbon emissions in kilograms (kg) (Karjalainen, 2011). Thus, as is the case for product labeling, understanding of this information is likely to be limited.

Although understanding of carbon information may be generally poor, there are likely to be individual differences which influence consumers' attention to and comprehension of this information. For instance, individuals who show higher concern for the environment may be more likely to support, understand, and/or be impacted by carbon labels (Rondoni & Grasso, 2021; Upham et al., 2011). Another potentially important individual difference variable is carbon numeracy.

Carbon numeracy. The literacy of numbers, numeracy, refers to one's ability to deal with and make sense of numbers and mathematical comparisons (Steen, 1990; Parsons & Bynner, 2005). Numeracy has been shown to play an important role in health care communications. Health care patients often must apply quantitative information to assess concepts like probability and risk when deciding a course of treatment. Generally, higher levels of numeracy are associated with an increased ability to interpret treatment benefits, increased understanding of the importance of preventative health behaviors, and increased assessment of disease/illness risks (Rothman et al., 2008). More broadly, numeracy is a strong predictor of decision-making skills (Cokely et al., 2018). Some research has examined the importance of numeracy in the context of climate change and climate impact messaging, though less so than in the context of healthcare. Hart et al. (2013) found that numeracy moderated the impact of numeric versus non-numeric climate change messages on intent to donate to environmental organizations such that individuals with low numeracy were more impacted by numeric messages than individuals with high numeracy.

Carbon numeracy includes the specific ability to understand and interpret quantitative representations of the carbon footprint of a behavior or purchase (Wynes et al., 2020). Research thus far on carbon numeracy has found an overall lack of carbon numeracy in participants (Wynes et al., 2020; Grinstein et al., 2018). Thus, despite an increase in exposure to GHG emission information, individuals are not necessarily able to apply this information in a way that would influence their own behavior. In addition to individual differences like numeracy, variable forms of presenting information can also affect their effectiveness – a prime example of which is framing.

Message Framing

Message framing stems from psychology's prospect theory, a model of decision-making which states that individuals code choice outcomes as gains or losses compared to a reference point. Further, according to prospect theory, it is through this evaluation of gains and losses that an individual will make their judgment (Kahneman & Tversky, 1979). The goal of message framing, then, is to influence the audience's perceptions of the gains and losses associated with a behavior (Rothman & Salovey, 1997). Pro-environmental behaviors are associated with various potential losses including monetary cost and inconvenience compared to a gain of environmental savings. For instance, an individual deciding what time to run their dishwasher might perceive lower GHG emissions as a gain, but they would also perceive potential losses such as not having their dishes clean as soon as they need them. A successful environmental message, then, would be framed in a way that makes the audience perceive greater environmental gain than their personal loss. This is particularly meaningful because research has found that consumers across the world are willing to pay more (though not a lot more) for sustainable products (Wei, et al., 2018).

In addition to influencing perception on gains and losses, how a message is framed can also interact with the audience's attitudes and behaviors by making the targeted belief available, accessible, and strong in the audience's memory (Chong & Druckman, 2007). Framing a message requires one to select key information and convey it in a way that increases the message's salience in the audience's mind. For instance, a message that emphasizes environmental feedback, rather than monetary feedback, appeals to the audience's altruistic motives which are likely less sensitive to the magnitude of the savings offered by the behavior change (Heyman & Ariely, 2004; Dogan et al., 2014).

Research on message framing shows that framing the avoidance of a negative consequence is often more effective than framing the gain of a positive consequence and this holds true with the framing of environmental behaviors specifically (Tversky & Kahneman, 1981; Morton et al., 2011). Morton et al. (2011) found that a climate change message that highlighted loss avoidance via pro-environmental behaviors was more effective than a message that highlighted environmental costs of climate change; in fact, the latter, negative messaging resulted in *decreased* pro-environmental behavioral intentions. In the context of household energy behavior, a loss avoidance frame that emphasizes decreased CO_2 emissions should be more effective than a gain-frame.

Communicating environmental losses and gains

Much of the environmental messaging that consumers face is presented as either simple savings of negative environmental effects or simple losses, such as GHG emissions associated with a given product. The effectiveness of these messages, though, is not well known. Furthermore, it is not clear whether there is an ideal way to frame information to consumers in a way that maximizes both the understanding and perception of the cost/savings. For instance, GHG savings are often presented in terms of metric tons or grams of CO_2 equivalent, but they can easily be converted into a myriad of different units of measurement that may well be easier to contextualize for an individual when contemplating their own behavior. Zapico et al. (2011) piloted a website on carbon literacy where users could convert CO_2 emissions into 23 different equivalencies (such as number of bananas or mobile phone charges required to emit the same amount of CO_2). The piloted website attracted thousands of visitors and received positive feedback from participants. However, whether one or some of these equivalencies is more impactful than the others was not investigated, and behavior change was not a goal of their study and, thus, was also not investigated. Climate communication researchers emphasize the importance of clear and familiar language (Corner et al, 2018). Because carbon information can be difficult to interpret, its presentation could make the difference between a person acting on or ignoring the information.

Thus, while the message content is important, how the message is framed also plays a role in the effectiveness of the message (Stern, 1992). It is crucial, then, to understand alternate ways of presenting climate impact information. The present study explores how to frame climate impact information in ways that are more useful, interpretable, and impactful. The current research tests the effectiveness of four different climate impact messages: one message is non-numerical ("more environmentally friendly"), while the other three are numeric representations and equivalencies of CO_2 savings (i.e., percentage, pounds, and square feet of forest).

GHG Emissions, Residential Energy, and Demand Response

A variety of behaviors, ranging from food purchases to recycling can impact an individual's carbon footprint. However, in the United States and globally, most GHG emissions are released during the burning of fossil fuels for energy uses such as electricity generation and transportation (74% of U.S. greenhouse gas emissions and 75% of global greenhouse gas emissions) (U.S. EIA, 2021a; U.S. EPA, 2021a). The combustion of fossil fuels that are high in carbon, such as natural gas, coal, and petroleum, results in the formation of carbon dioxide, water, and heat. While heat is used for energy, CO_2 is released into the atmosphere where some of it will remain for hundreds of years (U.S. EPA, 2021a). In contrast, the production of energy from renewable sources, such as wind, solar, geothermal, hydropower, and biopower emits zero GHG emissions (excluding the required infrastructure) (U.S. EPA, 2021b).

In 2020, renewable resources accounted for just 12% of electricity consumption in the United States, while nearly 80% came from fossil fuels, mainly natural gas and petroleum (the other 8% came from nuclear) (U.S. EIA, 2021b). However, meeting electricity demand across the U.S. with energy generated from renewable resources is a realistic goal. A study conducted by the National Renewable Energy Laboratory found that, by 2050, 80% of electricity generation in the U.S. could be sourced from renewable energy resources (Hand et al., 2012). To achieve this stronger reliance on renewable energy nationwide, however, markets will need to adopt a more flexible operating system that includes management of supply and demand timing. Thus, consumer behavior is crucial for the successful transition to renewable energy generation.

Demand response programs offer a promising route to greater energy flexibility by shifting demand *toward* periods of high generation and *away* from periods of high load (National Renewable Energy Laboratory, 2015). One model of demand response is variable pricing. Historically, utility companies charged consumers an average price that did not take into account the time of use. Smart metering infrastructure, however, has enabled variable pricing including time-of-use pricing and real-time pricing. Utility companies use variable pricing programs to encourage consumers to shift their energy usage to times when the price of supplying energy is lower (Mohsenian-Rad & Leon-Garcia, 2010). Although the main motivation behind introducing flexible pricing programs has been the optimization of revenue for utility companies, variable pricing structures have the potential for reducing environmental impact, by shifting consumer demand to times when electricity is being generated by renewable resources (Raghav et al., 2022; U.S. Department of Energy, 2015).

California already communicates this timing and aligns its time-of-use pricing accordingly (Energy Upgrade California, n.d.). However, this is not necessarily the norm for energy grids nor utility companies' communications. For example, 2017 energy source data from Fort Collins, Colorado (which has time-of-use pricing for energy consumption) revealed that off-peak pricing actually conflicts with the town's renewable usage. That is, Fort Collins Utilities charges the highest rate per kilowatt hour when renewables are at their highest percent share of energy generation. Fort Collins' price signal, then, encourages energy consumption at a time when *less* renewable energy is being used. Importantly, however, the average household consumer is not aware of the timing of renewable energy production in their local energy grid and, thus, can only base their energy consumption decisions on their own preferences and the pricing information they receive (i.e., if they are in an area with flexible pricing). The present study investigates the potential impact of a form of demand response that seeks to change consumption in a way that minimizes environmental impact.

Consumers balance a variety of preferences when it comes to household energy usage including monetary costs, convenience, comfort, and environmental impact (Aloise-Young et al., 2021). While price is, of course, a factor for consumers, it is often not the most important factor. In some cases, environmental savings of pro-environmental behaviors have proven to be more motivating than financial savings of the same behaviors (Dogan et al., 2014). In the context of residential energy consumption, comfort, convenience and behaving in a way that aligns with one's beliefs are often more important to consumers as they make decisions about running their homes (Kantola et al., 1984; Shove, 2003; Zipperer et al., 2013). In fact, when Jain et al. (2020) asked participants about purchase criteria for various categories of purchases, respondents cited sustainability as an important criterion in the category of electricity at a higher rate than any other category (37% said slightly important and 38% said extremely important).

The current study

Residential energy usage makes up 22% of all energy consumption in the U.S. (U.S. EIA, 2021a). More than half of this residential energy goes to heating and cooling homes, and almost 20% of it is for water heating (i.e., hot water for dishes, laundry, and showers) (U.S. EIA, 2015). Thus, household energy usage is an important and frequent target of pro-environmental behavior change and a viable target to help reduce climate change. Because of its potential impact, I chose household energy behavior – specifically the time of use of certain appliances – to be the target of the different climate impact messages in this study.

The research questions for the current study are:

1. Do different climate impact messages affect participants' likelihood of switching the time at which they run three appliances (dishwasher, washing machine, and air conditioning) toward a time of day when more renewable energy is available?
2. Does numeracy impact the effectiveness of the climate impact messages?

METHOD

Overview

The present study explored the effectiveness of four climate impact messages on household energy behavior. Two pilot tests were conducted previously to aid in the selection and refinement of the measures and procedures. The present study was conducted via an online study administered between July and October of 2022. Approval was received from the Colorado State University IRB.

Pilot studies

Message Selection. A preliminary survey was conducted with 48 students in an Environmental Psychology class at Colorado State University who were compensated with extra credit. The environmental savings that could be achieved when running the dishwasher, doing the laundry, and using the air conditioning at the most environmentally friendly time were calculated. These savings were expressed as CO_2 in grams, percent savings, miles driven equivalency, and forest planted equivalency. Participants were presented with these environmental savings (which were, in fact, equivalent) and asked to rank them from most environmentally friendly to least environmentally friendly. Participants in this preliminary survey rated the percent change and forest planted equivalency as the two most environmentally friendly choices. The amount of CO_2 saved in miles driven equivalency was rated as least environmentally friendly across all three appliances and the amount of CO_2 saved in grams was rated third on average. Based on these results, I chose to include the percentage and amount of CO_2, and square feet of forest planted as the three numerical conditions alongside a non-numerical condition described only as “more environmentally friendly.”

Effect size. The survey for the present study was piloted via Amazon MTurk (n = 161) by adding selected questions to a survey for another study on demand response. I ran individual ANOVAs for each appliance and calculated the effect sizes of the differences between conditions per appliance (see Tables 1-3).

Table 1
Dishwasher

	df	Sum Sq	Mean Sq	F	p	η2
Condition	3	6.95	2.32	1.78	0.16	0.04
Residuals	117	152.16	1.30			

Table 2
Washing Machine

	df	Sum Sq	Mean Sq	F	p	η2
Condition	3	9.59	3.2	3.03	0.03*	0.08
Residuals	105	110.85	1.06			

Table 3
Air Conditioning

	df	Sum Sq	Mean Sq	F	p	η2
Condition	3	8.37	2.79	2.18	0.10	0.11
Residuals	55	70.37	1.28			

With the lowest effect size (η2 = 0.04), I conducted a power analysis using Murphy et al. (2014)'s degrees of freedom of error calculations. To detect an effect size of 0.04, a sample size of 167 participants is needed with a power of 0.80 (Alpha = 0.05). As a result, we planned to continue data collection until 167 participants had completed the questions for each of the three appliances.

Present study

Participants. Participants were recruited through Reddit, a community-based social media site, and through environmental community group listservs. Characterized by various sub-communities for a myriad of topics (called “subreddits”), Reddit is considered an effective tool for social scientists to collect inexpensive, high-quality data from large samples (Jamnik & Lane, 2017; Shatz, 2017). The Reddit population skews American, male, and young, with about 64% of users between the ages of 18 and 29 years old (Amaya et al., 2021; Barthel et al., 2016). However, research comparing data collected via Reddit versus data collected via other more traditional sources (i.e., undergraduate college student populations) found that the Reddit data was at least as viable, if not more diverse (Jamnik & Lane, 2017; Shatz, 2017). Reddit consists of over 138,000 subreddits which allows researchers to target specific sub-populations that will have more relevance to, and be more engaged in, the study’s research objective (Amaya et al., 2021). As such, I targeted specific subreddits for this survey’s recruitment, including r/environment, r/environmentalism, r/energy, and the more general subreddit specifically for survey recruitment, r/samplesize. For the same reasons, I also reached out to specific community organizations with environmental and energy-related missions. Community groups that shared the survey with their members included American Energy Society, Colorado Renewable Energy Society, and CSU’s Energy Institute. All participants were consented before taking the survey. Data collection continued until data were obtained for each of the three appliances from167 participants (all of whom passed an attention check question). The survey in its entirety, as presented to participants, can be found in Appendix A.

Survey. The survey focused on participants’ willingness to switch their use of home appliances from less environmentally friendly times to the most environmentally friendly time (9 a.m.). This time was chosen based on hourly energy generation data for the United States (excluding Hawaii and Alaska) from summer 2021 (EIA, 2022). At 9 a.m. on an average summer day, about 36.97% of energy production across the lower 48 states is from non-fossil fuel sources (i.e., solar, wind, hydro, and nuclear), compared to 31.67% at 10 p.m., which is the lowest share of non-fossil fuel sources.

The survey included questions about three household appliances (dishwasher, washing machine, and air conditioning). Research has shown that kitchen and laundry behaviors are the most promising targets of behavioral demand response programs (Aloise-Young, et al., 2021; Hobman et al., 2017). Air conditioning was included because temperature control (space heating and air conditioning) accounts for more than half of household energy usage (U.S. EIA, 2015). Moreover, many automated demand response programs focus on controlling the air conditioning load.

Participants were first randomly assigned to one of the four messaging conditions. For each appliance, participants were asked a) whether they own and use the appliance, b) the most convenient time of day for them to run each appliance, and c) a baseline question asking the likelihood of switching the time that they run each appliance to 9 a.m. (assuming the same cost), with no environmental messaging present. Then, they were asked the likelihood of switching toward a more sustainable time of day (9 a.m.) for running each applicable appliance.

Note that, as shown in Figure 4, participants were only asked about their likelihood to switch if they reported having and using the appliance in question and if they did not select 9 a.m. as the most convenient time for them to run the appliance. In order to minimize barriers to switching their run time, participants were asked to assume they own smart appliances. Smart appliances allow users to set when they want their appliances to run ahead of time. Thus, owning smart appliances should decrease some inconvenience faced by consumers changing when they run their appliances. For instance, a smart dishwasher allows the user to select a delayed start, so they can load their dishwasher and have it automatically run hours later. Similarly, a smart thermostat allows the user to set different temperatures throughout the day. In the context of the present study, this means that the consumer would not necessarily need to be home at the time it is best to run it based on non-fossil fuel energy sources.

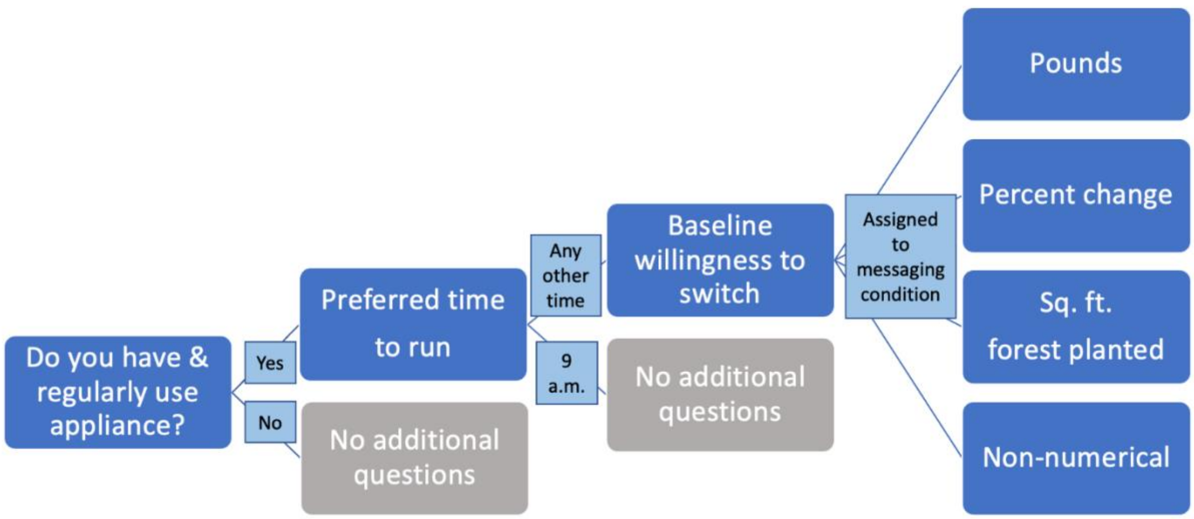

Figure 4. Visualization of the survey path participants followed for each appliance.

Messaging Conditions. Based on the 2021 hourly energy generation data from the U.S. Energy Information Administration, I calculated the average amount of CO_2 emissions associated with running each appliance in the summer at 9 a.m. (highest percentage of electricity generated by non-fossil fuel sources) and 10 p.m. (highest percentage of fossil fuel generation). The difference between these two values constitutes the emissions savings from switching the time the appliance runs. Emissions estimates were calculated based on the generation mix and typical power ratings for appliances were obtained from previous research (Kadavil et al., 2018).

Dishwashers and washing machines were assumed to run for 45 minutes, while air conditioning was assumed to run for 2 hours.

I then converted these CO_2 emission savings estimates into miles not driven by a gas-powered passenger vehicle (used only in the pilot study) and square feet of forest planted using the Greenhouse Gases Equivalencies Calculator provided by the U.S. Environmental Protection Agency (US EPA, n.d.). Percentage difference from 10 p.m. to 9 a.m. was also calculated. In addition to three numerical savings messages, a nonnumerical message described running appliances at 9 a.m. as 'more environmentally friendly.'

Messages were presented to participants with the language, "Assuming the same cost, if running your [appliance] at 9 am [insert condition-specific message], how likely would you be to switch to running your [appliance] at 9 am in the next year?" Response options were on a slider scale from 1 (*not at all likely*) to 5 (*extremely likely*), with participants able to select any number between 1 and 5 to the first decimal place (i.e., 1.1, 3.4, 4.8). The message conditions are shown in Table 4.

Table 4
Experimental messaging conditions

	Dishwasher	Washing Machine	Air Conditioning
Condition 1 – Pounds "…would cut the yearly CO2 emissions caused by your	dishwasher **by 6 pounds**…"	washing machine **by 14 pounds**…"	air conditioning **by 148 pounds**…"
Condition 2 – Percent Change "…would cut the yearly CO2 emissions caused by your	dishwasher **by 8.42%**…"	washing machine **by 8.42%**…"	air conditioning **by 8.42%**…"
Condition 3 – Forest "… would cut the yearly CO2 emissions caused by your	dishwasher **by the equivalent of planting 148 square feet of forest**…"	washing machine **by the equivalent of planting 329 square feet of forest**…"	air conditioning **by the equivalent of planting 3,476 square feet of forest**…"

Condition 4 – Non-numerical	"…was more environmentally friendly…"	"…was more environmentally friendly…"	"…was more environmentally friendly…"

Numeracy. Numeracy information was collected to test whether it plays a role in the effectiveness of the messages. In the present study, participants' numeracy was assessed with the Subjective Numeracy Scale (SNS), developed by Fagerlin et al., 2007. The SNS has eight items on a 6-point Likert scale. Four items assess perceived cognitive abilities with questions such as "How good are you at working with percentages?" and the other four items assess preference for display of numeric information with questions such as "When reading the newspaper, how helpful do you find tables and graphs that are parts of a story?" and "When you hear a weather forecast, do you prefer predictions using percentages (e.g., 'there will be a 20% chance of rain today') or predictions using only words (e.g., 'there is a small chance of rain today')?" Thus, unlike objective numeracy scales, in which participants are asked to solve numerical problems, the SNS measures participants' perceived numeracy. The SNS was developed in response to a number of issues associated with objective numeracy scales such as participant discomfort, larger cognitive load on participants, and more time needed to take the survey, all of which might lead to lower response rates. Fagerlin et al. (2007) report a Chronbach's alpha of 0.82 for the SNS and found a significant correlation between the SNS and an objective numeracy measure ($r = 0.53$, $p < 0.01$).

Barriers. Participants were also asked about reasons for not switching the time they run their appliances. Participants were given a list of eight potential barriers and were asked to rate the extent to which each barrier was true for them for each of the three appliances. Response options were presented on a Likert scale from "Not true for me" to "Extremely true for me." Barriers were based on participants' responses in a previous research study to open-ended questions about challenges they face for various pro-environmental behaviors (Ross, 2022). Barriers included not being home at 9 a.m., the time being inconvenient, lacking personal benefit, and lacking an understanding of the environmental impact.

Attention checks. One question was added to confirm participants were reading the questions closely. Within the barriers section, one statement read “Please select Extremely true for me for this statement.” Individuals who did not select “Extremely true for me” were excluded from the final sample.

RESULTS

Descriptives

Participation. A total of 379 participants provided data. Of these, 110 failed to complete the entire survey and 29 failed the attention check question. Each appliance was treated as its own dataset and, thus, an individual's data was included as long as they passed the attention check question and answered all questions for any appliance (for example, if an individual did not have air conditioning nor a dishwasher, but did have a washing machine, their responses to the washing machine questions were included). Specifically, of the 110 participants who did not complete the entire survey, 4 were still included in the analysis. This resulted in a final sample size of 244 participants who passed the attention check and responded to questions for at least one of the three appliances.

Appliances. Within the final sample, 51 participants did not have a dishwasher in their home that they use at least once a month; 10 did not have a washing machine in their home that they use at least once a month; and 57 did not have air conditioning in their home that they run at least once a month in the summer. Participants only answered questions about the appliances that they said they had in their home and used at least once a month. Participants who said they already preferred to run an appliance at the target time of day (9 a.m.) also did not answer questions about that appliance. Frequency distributions of the preferred times to run each appliance can be seen in Figures 5-7.

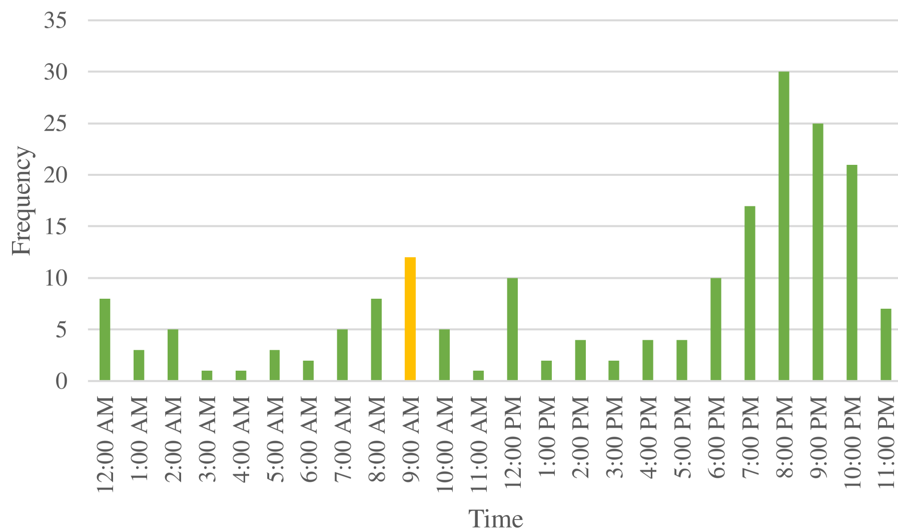

Figure 5. Preferred times to run dishwasher.

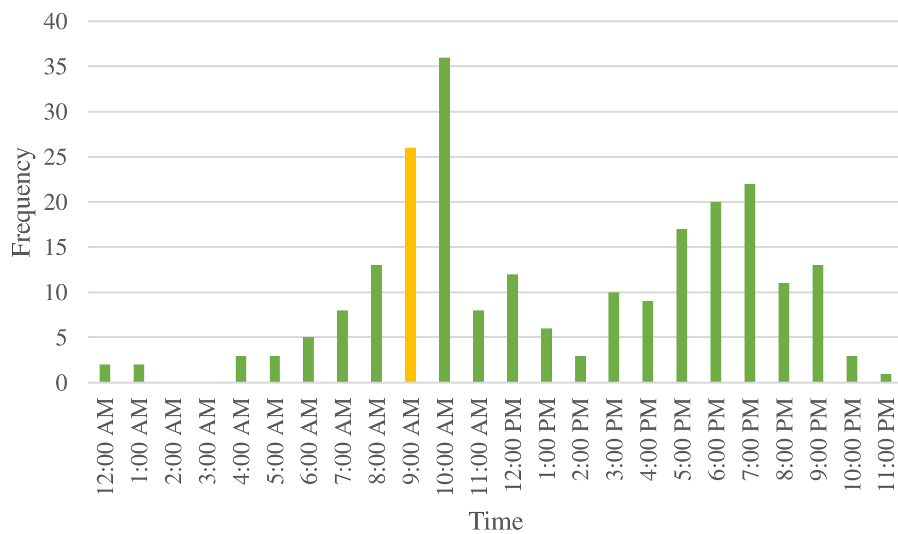

Figure 6. Preferred times to run washing machine.

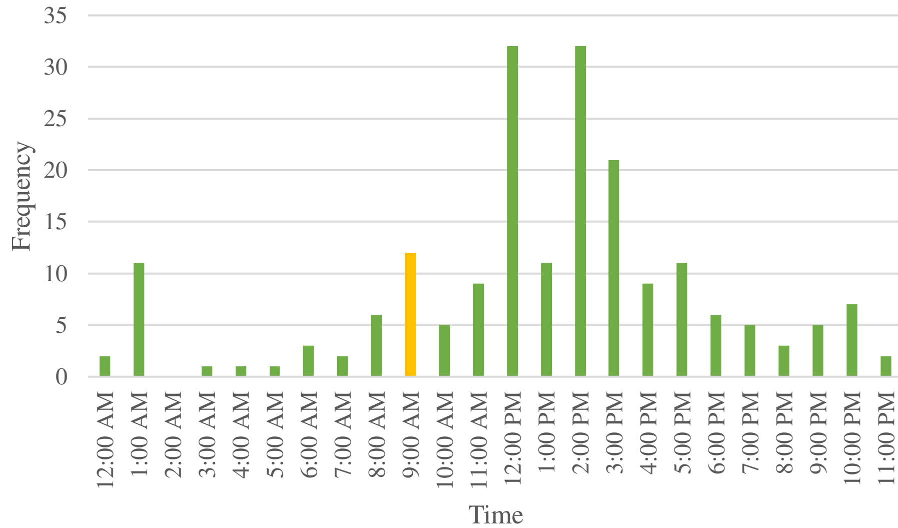

Figure 7. Preferred times to run air conditioning.

Each participant was randomly assigned to the same condition for all the appliances they answered questions about. The resulting breakdown of participation across appliances and conditions is shown in Table 5.

Table 5
Participant distribution across appliance and condition

	Dishwasher	Washing Machine	Air Conditioning
Pounds	54	62	51
Percent	36	40	32
Forest	47	56	48
Non-numerical	41	49	43
Total	**178**	**207**	**174**

Baseline likelihood. Participants were asked the likelihood of switching the time that they run each appliance to 9 a.m. (without any message present). Their responses were treated as a baseline likelihood to control for in the analysis. Descriptive statistics of this baseline likelihood are presented in Table 6. Baseline likelihood scores for dishwasher and washing machine were highly correlated with each other ($r = 0.74$, $p < 0.001$). Baseline likelihood scores for dishwasher and air conditioning were moderately correlated with each other ($r = 0.40$, $p < 0.001$), as were scores for washing machine and air conditioning ($r = 0.30$, $p < 0.001$). This lack of independence between baseline and experimental likelihoods confirms the need to control for participants' baseline likelihoods in the analysis.

Table 6
Mean baseline likelihood of switching the time appliance is run (on a scale from 1 to 5)

	Mean	SD
Dishwasher	2.57	1.38
Washing machine	3.55	1.48
Air conditioning	2.19	1.36

Numeracy. The mean numeracy score across the sample was 4.55 (SD = 0.96) with a minimum score of 1.5 and a maximum score of 6. For analyses, I coded numeracy as a dichotomous variable (high or low) with scores ≤4 coded as low and scores >4 coded as high. 25.87% of the sample had low numeracy scores and 74.13% had high numeracy scores.

Experimental likelihood. Participants were presented with one of four experimental messages and then, again, asked the likelihood of switching the time they run their appliances toward a more sustainable time of day. Descriptive statistics of this likelihood to change behavior are presented in Figure 8. For each appliance, this likelihood of changing one's behavior after being presented an experimental message was moderately correlated with participants' baseline likelihood (dishwasher: $r = 0.54$, $p < 0.001$; washing machine: $r = 0.50$, $p < 0.001$; air conditioning: $r = 0.65$, $p < 0.001$). Thus, baseline likelihood was included in subsequent analyses as a control variable.

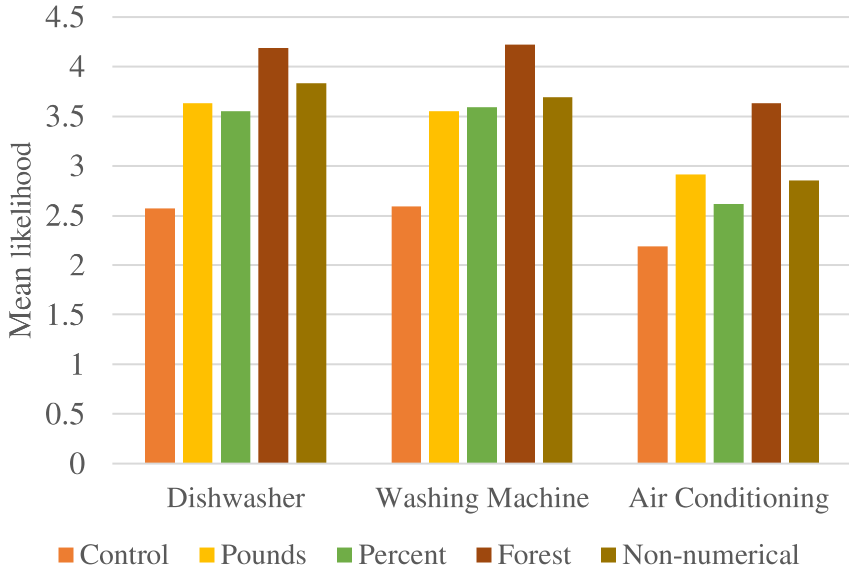

Figure 8. Mean likelihood of switching the time appliance is run (on a scale from 1 to 5).

Data Analysis

All analyses were conducted using the statistical software *R*. I used analysis of covariance (ANCOVA) to compare post-test likelihood of switching the time participants run each appliance across conditions and to test whether numeracy played a moderating role, while controlling for participants' baseline likelihood (no environmental message). Because participants' baseline willingness to change their behavior and their willingness after they were given an experimental message were correlated with each other, including the baseline likelihood as a covariate improves statistical power by accounting for more variation that would have otherwise been left unexplained as error (Porter & Raudenbush, 1987).

I ran individual ANCOVAs for each appliance, with the post-test likelihood as the outcome variable and messaging condition and numeracy as predictor variables. Likelihood of switching was treated as a continuous variable and messaging condition and numeracy were both treated categorically. Messaging condition and numeracy were input as an interaction term, which tested for the main effects of both variables and the interaction between them. Across all three appliances, neither the main effects of messaging condition and numeracy nor the interaction between the two were significant predictors of post-test likelihood (see results in Tables 7-9). However, as Figure 8 shows, there was a consistent pattern across the appliances, with the forest condition having the highest mean.

Table 7
ANCOVA results for dishwasher

Source	SS	F	η2
Condition	0.717	0.162	0.002
Numeracy	3.909	2.650	0.011
Baseline	85.387	57.898***	0.233
Condition x Numeracy	4.541	1.026	0.124

*** $p < 0.001$

Table 8
ANCOVA results for washing machine

Source	SS	F	η2
Condition	7.849	1.799	0.020
Numeracy	1.894	1.302	0.005
Baseline	77.912	53.564***	0.201
Condition x Numeracy	0.904	0.207	0.002

*** $p < 0.001$

Table 9
ANCOVA results for air conditioning

Source	SS	F	η2
Condition	1.845	0.436	0.006
Numeracy	3.063	2.172	0.009
Baseline	120.404	85.387***	0.356
Condition x Numeracy	0.866	0.205	0.003

*** $p < 0.001$

An additional question of interest was whether the experimental messaging did increase peoples' likelihood to change their behavior, even if the type of messaging did not have a significant impact. To test this question, I ran mean differences tests comparing baseline vs. experimental likelihood for each condition. I first calculated change scores for each individual's likelihood of changing behavior by subtracting each participants' baseline likelihood from their experimental likelihood for each appliance. I then averaged each participant's change score across appliances to account for the fact that some participants were only eligible to answer questions for some appliances. Finally, I ran individual t-tests for each experimental condition testing the null hypothesis that the average change-in-likelihood score (averaged across all appliances) was equal to 0 (see results in Table 10). Descriptive statistics of experimental likelihood compared to baseline likelihood are presented in Figure 8. For each experimental condition, there is strong evidence that, on average, the difference between the experimental likelihood and baseline likelihood was significantly greater than 0.

Table 10
T-test results for change in likelihood

Condition	Mean	SD	df	t-statistic
Pounds	0.941	1.143	60	6.428***
Percent	0.747	1.061	37	4.343***
Forest	1.346	1.276	59	8.168***
Non-numerical	1.066	1.175	51	6.544***

*** $p < 0.001$

Barriers

Barriers were assessed on a 5-point Likert scale from "Not true for me" to "Extremely true for me." Response options were coded as ordinal (1-5). Descriptive statistics were obtained for each set of barriers per appliance. Frequencies of reporting a barrier as true (either slightly true, moderately true, very true, or extremely true) are reported in Table 10.

Dishwasher barriers. The barrier to switching the time participants run their dishwasher that was rated as most true across participants (mean = 2.45, SD = 1.54) was "I'm not home at 9 a.m." while the second most true (mean = 2.12, SD = 1.35) was "I don't have control over it or am not solely in charge of it (e.g., another household member runs it)." The barrier that was rated as least true across participants (mean = 1.35, SD = 0.93) was "It costs more money at 9 a.m."

Washing machine barriers. The barrier to switching the time participants run their washing machine that was rated as most true across participants (mean = 2.47, SD = 1.57) was also "I'm not home at 9 a.m." and the second most true (mean = 2.14, SD = 1.35) was also "I don't have control over it or am not solely in charge of it (e.g., another household member runs it)." The barrier that was rated as least true across participants (mean = 1.33, SD = 0.90) was "I'm not interested in changing my environmental impact."

Air conditioning barriers. The barrier to switching the time participants run their air conditioning that was rated as most true across participants (mean = 3.15, SD = 1.61) was "It's uncomfortable to have it cooler at 9 a.m. and/or warmer at other times" while the second most true (mean = 2.57, SD = 1.52) was "There isn't enough personal benefit to me." The barrier that was rated as least true across participants (mean = 1.38, SD = 0.96) was also "I'm not interested in changing my environmental impact."

Table 11
Frequency of rating each barrier as "[Slightly/Moderately/Very/Extremely] true for me"

	Dishwasher		Washing Machine		Air Conditioning	
	n	%	n	%	n	%
I'm not home at 9 a.m.	134	55.37%	133	56.84%	114	50.44%
It's inconvenient to not have clean laundry/dishes at 9 a.m.	111	45.49%	98	42.06%	-	-
It's uncomfortable to have it cooler at 9 a.m. and/or warmer at other times	-	-	-	-	162	71.68%
It costs more money at 9 a.m.	35	14.52%	43	18.62%	44	19.64%

There isn't enough personal benefit to me	107	48.15%	105	45.06%	136	60.71%
The environmental impact isn't large enough	115	47.13%	97	41.45%	81	36.32%
I don't have control over it or am not solely in charge of it (e.g., another household member runs it)	120	49.38%	115	49.15%	98	43.75%
I don't understand the environmental impact	97	39.75%	92	39.49%	75	33.63%
I'm not interested in changing my environmental impact	46	19.33%	38	16.38%	39	17.81%

Additional barriers. Participants were also offered an optional "Other" barrier, that they could fill in and rate on the same 5-point Likert scale. The most common theme participants added with regards to running their dishwasher had to do with their daily routine and work schedule. For instance, multiple individuals noted that they work from home and the dishwasher makes too much noise and multiple individuals noted that they are typically asleep at 9 a.m. Other themes noted for dishwasher barriers included not actually owning smart appliances and preferring to run the dishwasher as soon as it is full.

The most common theme for the optional open-ended barriers for washing machines was the need to dry clothing quickly after the wash cycle. Daily routine and work schedule was also mentioned by multiple participants as a barrier to changing the time it is run.

As for air conditioning, the most common additional barrier mentioned by participants by far was about timing, specifically that 9 a.m. is not the most helpful time to be running air conditioning because it is typically not the hottest period of the day. Many participants also specifically mentioned preferring to run their air conditioning at night to aid in better sleep.

Barriers as a function of likelihood of switching. To look further into the barriers that individuals face when it comes to running household appliances at a different time, I also split the data into two groups to compare: those who were "extremely unlikely" to change the time they run each appliance and those who showed any level of likelihood of changing their behavior.

For air conditioning, both groups rated the same barrier as most true ("It's uncomfortable to have it cooler at 9 a.m. and/or warmer at other times"), though those who were extremely unlikely to change their behavior rated the barrier higher on average (mean = 4.05, SD = 1.53 compared to mean = 3.43, SD = 1.42).

For dishwasher, the barriers that were rated as most true differed between the two groups. For those who were extremely unlikely to change their behavior, the two barriers "There isn't enough personal benefit to me" (mean = 3.10, SD = 1.73) and "The environmental impact isn't large enough" (mean = 3.10, SD = 1.67) were tied for the highest rating. For those who showed any level of likelihood of change their behavior, "I'm not home at 9 a.m." was rated as most true (mean = 2.46, SD = 1.47).

For washing machine, both groups rated the same barrier as most true ("I'm not home at 9 a.m."), though those who were extremely unlikely to change their behavior rated the barrier higher (mean = 3.67, SD = 1.68 compared to mean = 2.44, SD = 1.56).

DISCUSSION

The purpose of the present study was to investigate ways to better frame climate impact messages to increase their effectiveness in changing consumer behavior. This research question was specifically tested in the context of household energy behavior, which has a large greenhouse gas impact (U.S. EIA, 2021a; U.S. EPA, 2021a). Household energy behavior is a particularly important behavior as we shift toward a greater reliance on renewable energy, which requires increased flexibility on the consumer demand side (Raghav et al., 2022; U.S. Department of Energy, 2015). Four climate impact messages were tested: one that presented climate impact in terms of pounds of carbon, one in terms of percent carbon savings, one in terms of forest planted equivalency, and a non-numerical message. After answering the likelihood of changing their behavior when no messaging was present, participants were assigned to one of the four conditions for up to three household appliances.

Willingness to shift usage

In the present study, I sought to test two research questions: Would the four different climate impact messaging conditions show different effectiveness in increasing participants' likelihood of changing their behavior? And would numeracy play a moderating role in the effectiveness of the messages? This study was exploratory in nature and, thus, specific hypotheses were not advanced.

Across the four messaging conditions, participants did not show a significantly different likelihood of shifting the time they use their appliances. However, participants did show a greater likelihood to shift their appliance use when *any* environmental message was present. Participants were significantly more likely to change their behavior when presented with any environmental message compared to when no message was present, which reiterates the importance of studying climate impact messaging. The fact that an environmental message is impactful, paired with the motivation of consumers to behave more ethically, confirms that understanding which types of messages can be most effective in inspiring behavior change is an important research topic.

Regardless of messaging condition, participants were less likely to change their behavior when asked about switching the time they run their air conditioning, compared to both washing machine and dishwasher (whose results were more similar to each other). This trend is in line with previous literature suggesting that laundry and kitchen practices show greater energy flexibility than heating and cooling behaviors (Hobman et al., 2017). While use of air conditioning also has the highest environmental impact, it is a much less malleable behavior.

Across the three appliances, participants were more likely (albeit non-significantly) to change their behavior when shown forest equivalency messaging. This trend also emerged in the pilot study data for two of the three appliances (washing machine and dishwasher). Though non-significant, this trend may be worth further research, especially considering the potential ways it could be used. Compared to other numerical representations of climate impact, forest equivalency easily allows for another aspect of effective communications: visualizations. Imagery has long been suggested as a way to better convey an idea or message, especially in scientific communications (Trumbo, 1999). Research on climate change related communications specifically has found that imagery can increase the presented issue's saliency and participants' feelings of self-efficacy related to the issue presented (though, notably, few images seem able to do both) (O'Neill et al., 2013). Overall, research suggests that visuals, alongside text, play an important role in a message's persuasiveness (Lazard & Atkinson, 2015). Combining this literature with the trend found in this data, an important future direction could be testing the effectiveness of a forest equivalency climate impact message that incorporates a forest visualization. Additionally, future research may investigate other easily calculated and easy to visualize equivalencies (such as miles traveled by a gasoline-powered car, barrels of oil burned, etc.) to determine if one does perform significantly better than other messages.

Another important distinction between the messages tested in this study is their scalability: the pounds of CO_2 emissions and the equivalent of acres of forest planted are both messages that would scale up or down with the impact of the behavior, while the percentage and non-numerical messages do not. Similarly, normative messaging and color-coded messaging like the EU's mandatory energy efficiency label may help guide people to more environmentally friendly decisions, but they do not address the problem of people not *understanding* high versus low impact behaviors and products. People often underestimate the energy usage of many appliances and behaviors and are largely unknowledgeable when it comes to comparing energy used by different behaviors (Attari et al., 2010).

Numeracy

Numeracy did not play a significant role in the effectiveness of the environmental messages. One potential explanation for this is a lack of familiarity with carbon information such that carbon numeracy is consistently low, despite one's level of numeracy. In other words, considering numeracy as a moderator may not have been as important as *carbon* numeracy specifically, and the measure used was not necessarily a strong predictor of carbon numeracy. This is supported by previous research that suggests a lack of carbon numeracy in the public (Wynes et al., 2020; Grinstein et al., 2018). On the other hand, we did see overall high scores of numeracy in this sample (mean = 4.55, SD = 0.96), and the distribution of scores was sufficiently skewed that we were unable to achieve reasonably equal high- and low-numeracy groups. Thus, while there was no moderating effect of numeracy here, it may still be worth considering when it comes to other populations and samples.

Barriers

The barriers participants face when considering changing the times they run both their dishwasher and washing machine were most frequently about the time in question (9 a.m.) being incompatible with their daily schedules and routines. This suggests that smart homes, specifically smart appliances, which can automatically run at programmed times, may be a way to overcome this barrier to behavior change. However, a few participants did note a lack of trust when it comes to smart appliances. For example, one participant stated, “I have concerns about data security using smart devices.” To fully realize the benefits smart homes and appliances can provide, it is important to address concerns like this (Balta-Ozkan et al., 2013).

The barriers participants face when considering changing the time they run their air conditioning had to do with discomfort and inconvenience: 9 a.m. proved to be a suboptimal time to run air conditioning in lieu of other times, despite the environmental savings it could have. Unlike the most popular barriers for dishwasher and washing machine, this is not a barrier that smart homes would overcome. Thus, future research may examine ways to overcome this barrier, either on the energy production side (i.e., working to increase renewable production at warmer times of the day) and/or on the consumer behavior side (i.e., researching ways individuals can compensate for a home being too warm).

Limitations and future directions

Statistical power. A key limitation of this study was, surprisingly, a lack of statistical power. While we ran a power analysis on our pilot study data to try to prevent a power issue, the effect sizes found in the present study’s data were even smaller than that of the pilot study. (The smallest effect size in the pilot study analysis was $\eta 2 = 0.04$, whereas the smallest effect size in the present study was $\eta 2 = 0.002$.) A post-hoc power analysis revealed that, to achieve a power of 0.8 at a significance level of 0.05, the minimum sample size needed per condition to detect an effect size of 0.002 is $n = 5,445$. One possibility, then, is that the sample size obtained was still not large enough to detect any effect. We did not predict such a distinct difference in effect sizes between the two samples, but there are two potential drivers of this disparity. The first has to do with sample characteristics: because the sample of the present study was made up of environmentally minded individuals (which was not necessarily true of the pilot study sample), it is possible that the different messaging types have a smaller impact on this sample's behavior. Participants in the pilot study did rate the barrier "I'm not interested in changing my environmental impact" more highly (across all appliances) than those in the present study, which supports this theory. A second important difference between the pilot study and the present study was the targeted time to run appliances given to participants (9 a.m. in the present study and 5 p.m. in the pilot study). The justification for this change was that 5 p.m. was based on data from the city where study recruitment took place (Fort Collins, CO), whereas 9 a.m. was based on national data, but the change could nonetheless have impacted the study's effect size.

The differences between the present study and pilot study samples does inform an important future direction for climate impact researchingresearch: segmentation. Future research should collect demographic and lifestyle (i.e.g., a measure of environmental mindedness) data, in order to understand how and for whom certain impact messages are most effective,. This specific research goal could inform customized interventions based on certain traits of different consumers.

Other contexts. The context for the present investigation was energy flexibility. This choice of household energy behavior was made because of the large impact energy usage has on the environment. However, there are many other areas that carbon messaging research should explore. Another important context for carbon messaging is product purchasing behavior because, like household energy usage, consumer goods packaging is a space in which carbon impact information is already being communicated. Future research should also compare product labels with and without various messaging types. Furthermore, it would be worth investigating whether the effectiveness of messages differs across industries (e.g., beauty, food, household appliances).

Demand characteristics. Another limitation of this study is the possibility that participants, consciously or subconsciously, skewed their responses toward what they viewed as socially desirable. Given the nature of the survey questions, we were unable to disguise the nature of the study. Thus, participants would have been able to answer the questions in a way that made them appear more environmentally driven (i.e., responding with a higher likelihood of changing their behavior than what is truthful). However, we did see a range in participants' likelihood of switching their behavior across the appliances (with. Specifically, air conditioning showingshowed the lowest average likelihood) and, and 60.72% of participants ranked the barrier "There isn't enough personal benefit to me" as the second most true barrier they face when it came totrue for them for air conditioning. Both of these findings suggestThis suggests that there was not a strong social desirability effect at play in this sample.

Similarly, the operationalization of our dependent variable – self-reported likelihood of changing the time the participant runs their appliance – likely does not translate perfectly into what we would actually prefer to measure, which is actual change in behavior. The relationship between self-reported intention and actual behavior has been researched and discussed in social psychology research for decades (Ajzen, 1991; Ajzen & Fishbein, 1973). A meta-analysis of pro-environmental behavior change found a moderate correlation of r = 0.54 between intention and behavior but noted that the individual studies did vary considerably (Schwenk & Möser, 2009). Though self-report intentions are an imperfect measure of actual behavior, many behaviors (including energy usage and energy-related behaviors) are costly to measure. As utilities begin to transition to using environmental signals in addition to price signals (e.g., the UK's green light program), future research could measure behavior more effectively, which would also help minimize social desirability effects.

Message selection. While nonsignificant, the trend we saw was of the forest equivalent condition performing better than the other three messaging conditions. For all three appliances, the numbers in this condition were the largest (for example, running your dishwasher at 9 a.m. would cut the yearly CO2 emissions by 6 pounds, 8.42%, or 148 square feet of forest). Thus, it could have been the sheer magnitude of the numbers that was driving this trend. Future research should look at comparing two products or behaviors directly, with varying combinations of message type and magnitude, to determine if the magnitude of the numbers or the message type itself is predicting the effectiveness of the message.

Normative messaging is a common form of behavior change communication that was not included in the present study. Normative appeals are messages with information about social norms (i.e., what most people do or what people ought to do) (Cialdini et al., 1991). Normative messaging has proven effective for promoting some pro-environmental behaviors including decreased energy usage (Miller & Prentice, 2016). The present study did not include normative messaging in any of the conditions for a couple of reasons. First, the specific context for the present study (demand response) may not be well-suited to normative messaging. Specifically, a major goal of demand response is to move energy consumers away from peak times of usage (i.e., away from what most people do, or counter to the norm). Second, there are many examples of climate impact messages already being communicated to consumers with the specific intent of informing an already-motivated consumer base about the climate impact of certain behaviors and products (see Figure 2). It has been shown that consumers value decreased carbon emissions. Furthermore, not only do consumers want to be given carbon emission information, but, when shown the information, they also do use it to inform purchasing behavior (Groening et al., 2015). Climate impact information, then, is not used solely as a persuasive communication. Instead, providing information like the carbon emissions of a product or behavior enables consumers to make decisions that align with their own values and goals. The present study acknowledges the way climate impact information is increasingly being communicated and, thus, seeks to determine whether there are better ways to frame that information.

Conclusion

While this study did not yield significant results related to its two main research questions (whether there was a differential effectiveness between four different climate impact messages, and whether numeracy played a moderating role), there were still key findings worth examining further. First, the messages were effective in changing participants' likelihood of changing their behavior. This finding confirms that information can be effective in an already motivated population and solidifies the importance of this research overall. Second, the forest equivalency message consistently performed better than the other three messages, which is worth looking into more deeply because square footage of forest is easily visualized and because other equivalencies can be easily calculated and, thus, tested. Finally, the barriers the participants in this sample faced emphasizes the potential impact of smart homes and the need for further innovation in this realm.

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APPENDIX A

Survey Questions

Do you have a **dishwasher** in your home that you use at least once a month?

- ○ Yes
- ○ No

Do you have a **washing machine** in your home that you use at least once a month?

- ○ Yes
- ○ No

Do you have **air conditioning** in your home that you run at least once a month (in the summer)?

- ○ Yes
- ○ No

The next set of questions ask about your preferred time to run your dishwasher, washing machine, and air conditioning. For these questions, assume that you own SMART appliances. A SMART dishwasher/washing machine has a delayed start feature so that you can load the machine and set it to run at any time over the next 24 hours, even if you're not home or asleep.

A SMART thermostat allows you to set different temperatures for different times of day, so if you want to run your A/C at a certain time, you would set a cool temperature for that time of day.

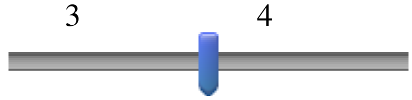
When is the **most convenient time to run your dishwasher on a weekday**, assuming that it would run for 45 minutes?

- ○ 12:00 AM (midnight)
- ○ 1:00 AM
- ○ 2:00 AM
- ○ 3:00 AM
- ○ 4:00 AM
- ○ 5:00 AM
- ○ 6:00 AM
- ○ 7:00 AM
- ○ 8:00 AM
- ○ 9:00 AM
- ○ 10:00 AM
- ○ 11:00 AM
- ○ 12:00 PM (noon)
- ○ 1:00 PM
- ○ 2:00 PM
- ○ 3:00 PM
- ○ 4:00 PM
- ○ 5:00 PM
- ○ 6:00 PM
- ○ 7:00 PM
- ○ 8:00 PM
- ○ 9:00 PM
- ○ 10:00 PM

○ 11:00 PM

Assuming the cost would remain the same, how likely would you be to switch to running your **dishwasher** at 9 a.m. in the next year?

Extremely unlikely					Extremely likely
1	2	3	4	5	6



When is the **most convenient time to run your washing machine on a weekday**, assuming that it would run for 45 minutes?

○ 12:00 AM (midnight)

○ 1:00 AM

○ 2:00 AM

○ 3:00 AM

○ 4:00 AM

○ 5:00 AM

○ 6:00 AM

○ 7:00 AM

○ 8:00 AM

○ 9:00 AM

○ 10:00 AM

○ 11:00 AM

○ 12:00 PM (noon)

○ 1:00 PM

○ 2:00 PM

○ 3:00 PM

○ 4:00 PM

○ 5:00 PM

○ 6:00 PM

○ 7:00 PM

○ 8:00 PM

○ 9:00 PM

○ 10:00 PM

○ 11:00 PM

Assuming the cost would remain the same, how likely would you be to switch to running your **washing machine** at 9 a.m. in the next year?

Extremely unlikely					Extremely likely
1	2	3	4	5	6

Assume that it is SUMMER and the high temperature is 86° F. When is the **most convenient time to run your air conditioning on a weekday**, assuming it will run for 2 hours?

- ○ 12:00 AM (midnight)
- ○ 1:00 AM
- ○ 2:00 AM
- ○ 3:00 AM
- ○ 4:00 AM
- ○ 5:00 AM
- ○ 6:00 AM
- ○ 7:00 AM
- ○ 8:00 AM
- ○ 9:00 AM
- ○ 10:00 AM
- ○ 11:00 AM
- ○ 12:00 PM (noon)
- ○ 1:00 PM
- ○ 2:00 PM
- ○ 3:00 PM
- ○ 4:00 PM
- ○ 5:00 PM
- ○ 6:00 PM
- ○ 7:00 PM
- ○ 8:00 PM
- ○ 9:00 PM
- ○ 10:00 PM
- ○ 11:00 PM

Assuming the cost would remain the same, how likely would you be to switch to running your **air conditioning** at 9 a.m. in the next year?

Extremely unlikely Extremely likely
1 2 3 4 5 6

Renewable sources of energy (such as wind, solar, and hydro) are increasingly being used to generate electricity across the U.S.

Renewables are more environmentally friendly than the traditional energy sources of coal and natural gas. One way to make greater use of renewable energy as an individual is to shift your energy usage to a time when a greater percentage of renewables is available. Nationally, 9 a.m. is the time when the greatest percentage of electricity is being generated by renewable sources.

Assuming the same cost, if running your dishwasher at 9 a.m. would **cut the yearly CO_2 emissions caused by your dishwasher by 6 pounds**, how likely would you be to switch to running your dishwasher at 9 a.m. in the next year?

Extremely unlikely Extremely likely
1 2 3 4 5 6

Assuming the same cost, if running your washing machine at 9 a.m. would **cut the yearly CO_2 emissions caused by your washing machine by 14 pounds**, how likely would you be to switch to running your washing machine at 9 a.m. in the next year?

Extremely unlikely Extremely likely
1 2 3 4 5 6

Assuming the same cost , if running your air conditioning at 9 a.m. would **cut the yearly CO_2 emissions caused by your air conditioning by 148 pounds**, how likely would you be to switch to running your air conditioning at 9 a.m. in the next year?

Extremely unlikely Extremely likely
1 2 3 4 5 6

Assuming the same cost, if running your dishwasher at 9 a.m. would **cut the yearly CO2 emissions caused by your dishwasher by 8.42%**, how likely would you be to switch to running your dishwasher at 9 a.m. in the next year?

Extremely unlikely					Extremely likely
1	2	3	4	5	6

Assuming the same cost, if running your washing machine at 9 a.m. would **cut the yearly CO2 emissions caused by your washing machine by 8.42%**, how likely would you be to switch to running your washing machine at 9 a.m. in the next year?

Extremely unlikely					Extremely likely
1	2	3	4	5	6

Assuming the same cost, if running your air conditioning at 9 a.m. would **cut the yearly CO2 emissions caused by your air conditioning by 8.42%**, how likely would you be to switch to running your air conditioning at 9 a.m. in the next year?

Extremely unlikely					Extremely likely
1	2	3	4	5	6

Assuming the same cost, if running your dishwasher at 9 a.m. would **cut the yearly CO2 emissions caused by your dishwasher by the equivalent of planting 148 square feet of forest,** how likely would you be to switch to running your dishwasher at 9 a.m. in the next year?

Extremely unlikely					Extremely likely
1	2	3	4	5	6

Assuming the same cost, if running your washing machine at 9 a.m. would **cut the yearly CO2 emissions caused by your washing machine by the equivalent of planting 329 square feet of**

forest, how likely would you be to switch to running your washing machine at 9 a.m. in the next year?

Extremely unlikely Extremely likely
1 2 3 4 5 6

Assuming the same cost, if running your air conditioning at 9 a.m. would **cut the yearly CO_2 emissions caused by your air conditioning by the equivalent of planting 3,476 square feet of forest**, how likely would you be to switch to running your air conditioning at 9 a.m. in the next year?

Extremely unlikely Extremely likely
1 2 3 4 5 6

Assuming the same cost, if running your dishwasher at 9 a.m. was **more environmentally friendly**, how likely would you be to switch to running your dishwasher at 9 a.m. in the next year?

Extremely unlikely Extremely likely
1 2 3 4 5 6

Assuming the same cost, if running your washing machine at 9 a.m. was **more environmentally friendly**, how likely would you be to switch to running your washing machine at 9 a.m. in the next year?

Extremely unlikely Extremely likely
1 2 3 4 5 6

Assuming the same cost, if running your air conditioning at 9 a.m. was **more environmentally friendly**, how likely would you be to switch to running your air conditioning at 9 a.m. in the next year?

Extremely unlikely Extremely likely
1 2 3 4 5 6

The next set of questions asks about your ability to work with numbers and your preference for numerical information.

How good are you at...

	Not at all good	Slightly good	Somewhat good	Quite good	Very good	Extremely good
working with fractions?	○	○	○	○	○	○
working with percentages?	○	○	○	○	○	○
calculating a 15% tip	○	○	○	○	○	○
figuring out how much a shirt will cost if it is 25% off?	○	○	○	○	○	○

When reading the newspaper, how helpful do you find tables and graphs that are parts of a story?

○ Not at all helpful

○ Slightly helpful

○ Somewhat helpful

○ Quite helpful

○ Very helpful

○ Extremely helpful

When people tell you the chance of something happening, do you prefer that they use words (‘‘it rarely happens’’) or numbers (‘‘there’s a 1% chance’’)?

- ○ Always prefer words
- ○ Mostly prefer words
- ○ Slightly prefer words
- ○ Slightly prefer numbers
- ○ Mostly prefer numbers
- ○ Always prefer numbers

When you hear a weather forecast, do you prefer predictions using percentages (e.g., ‘‘there will be a 20% chance of rain today’’) or predictions using only words (e.g., ‘‘there is a small chance of rain today’’)?

- ◯ Always prefer percentages
- ◯ Mostly prefer percentages
- ◯ Slightly prefer percentages
- ◯ Slightly prefer words
- ◯ Mostly prefer words
- ◯ Always prefer words

How often do you find numerical information to be useful?

- ◯ Never
- ◯ Rarely
- ◯ Sometimes
- ◯ A lot of the time
- ◯ Most of the time
- ◯ Always

The final set of questions asks about the reasons why you might not want to switch the time you run your appliances.

DISHWASHER

People have different reasons for not wanting to switch the time they run their **dishwasher**. How true are each of these reasons for you?

	Not true for me	Slightly true for me	Moderately true for me	Very true for me	Extremely true for me
I'm not home at 9 a.m.	○	○	○	○	○
It's inconvenient to not have clean dishes at 9 a.m.	○	○	○	○	○
It costs more money at 9 a.m.	○	○	○	○	○
There isn't enough personal benefit to me	○	○	○	○	○
The environmental impact isn't large enough	○	○	○	○	○
I don't have control over it or am not solely in charge of it (e.g., another household member runs it)	○	○	○	○	○
I don't understand the environmental impact	○	○	○	○	○
Please select Extremely true for me for this statement	○	○	○	○	○
I'm not interested in changing my environmental impact	○	○	○	○	○
Other	○	○	○	○	○

WASHING MACHINE

People have different reasons for not wanting to switch the time they run their **washing machine**. How true are each of these reasons for you?

	Not true for me	Slightly true for me	Moderately true for me	Very true for me	Extremely true for me
I'm not home at 9 a.m.	○	○	○	○	○
It's inconvenient to not have clean laundry at 9 a.m.	○	○	○	○	○
It costs more money at 9 a.m.	○	○	○	○	○
There isn't enough personal benefit to me	○	○	○	○	○
The environmental impact isn't large enough	○	○	○	○	○
I don't have control over it or am not solely in charge of it (e.g., another household member runs it)	○	○	○	○	○
I don't understand the environmental impact	○	○	○	○	○
I'm not interested in changing my environmental impact	○	○	○	○	○
Other	○	○	○	○	○

AIR CONDITIONING

People have different reasons for not wanting to switch the time they run their **air conditioning**. How true are each of these reasons for you?

	Not true for me	Slightly true for me	Moderately true for me	Very true for me	Extremely true for me
I'm not home at 9 a.m.	○	○	○	○	○
It's uncomfortable to have it cooler at 9 a.m. and/or warmer at other times	○	○	○	○	○
It costs more money at 9 a.m.	○	○	○	○	○
There isn't enough personal benefit to me	○	○	○	○	○
The environmental impact isn't large enough	○	○	○	○	○
I don't have control over it or am not solely in charge of it (e.g., another household member runs it)	○	○	○	○	○
I don't understand the environmental impact	○	○	○	○	○
I'm not interested in changing my environmental impact	○	○	○	○	○
Other	○	○	○	○	○

Where you currently live, does electricity cost different amounts at different times of the day?

○ Yes

○ No

○ Don't know

How often do you change the time that you run the following appliances to try to save money?

	Never	Sometimes	About half the time	Most of the time	Always
Dishwasher	○	○	○	○	○
Washing machine	○	○	○	○	○
Air conditioning	○	○	○	○	○