NUDGEABLE, TO A DEGREE:
AN EXPERIMENTAL EXAMINATION OF TEMPERATURE DEFAULTS IN UNIVERSITY RESIDENCE HALLS

by

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A thesis submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Master of Science in Water Science and Policy

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ABSTRACT

Air conditioning and heating are the two largest categories of residential energy use. We conducted a field experiment across 566 dorm rooms at the University of Delaware to test whether temperature setting defaults can be used to reduce energy consumption. Treatments, applied using a between-subject design, varied the default temperature and how frequently the default was reset. Post-experiment survey data are used to identify relevant psychological channels through which the default effect is activated, along with residents' emotional reactance to the default. Using difference-in-differences regression models, we find the presence of default effects in all treatments. This default effect appears to be primarily driven by the effort required to repeatedly change away from the default temperature, concern for others' comfort, and a lack of knowledge about how the dorm room thermostats work. Residents' perceptions of the experiment were neutral to slightly positive on average, but the welfare effects of the default remain unclear as some residents maintained default settings simply because they did not believe they could change the thermostat setting. A supplemental field experiment finds that, relative to the status quo, winter energy consumption and operating costs of the dorm room fan coil units can be cut 28% through more efficient heating setpoints, and an additional 9% through weekly reinforcement of a temperature default. These results demonstrate that small temperature defaults may be a promising way to reduce energy consumption and costs without provoking a negative response from occupants. Future research is needed to understand the effect of temperature defaults in warm seasons and to clarify welfare effects, particularly when residents lack understanding about how to operate their thermostats.

Chapter 1
INTRODUCTION

1.1 An Introduction to Defaults

A question central to sustainability research and policy is how to encourage individuals to make sustainable decisions. Although resource consumption decisions at the individual/household level may have minimal environmental consequences, impacts can be much greater in the aggregate when these decisions are made millions of times across a population (*e.g.*, Dietz et al., 2009). While sustainable decisions can be mandated via regulation or promoted with financial (dis)incentives, such approaches carry a risk of incurring substantial financial and/or political capital costs (*e.g.*, Benartzi et al. (2017); Carattini et al. (2017); Furceri, Ganslmeier and Ostry (2023); Zhang and Wang (2017)). An alternative approach involves modifying the environment of the decision in a way that will 'nudge' decision-makers towards a new choice (Dolan et al., 2012). It is important to note that these nudges encourage certain behaviors without removing the decision-maker's free will to behave as they wish. However, the impacts of many of these modifications are well enough studied that they can change aggregate behavior in predictable ways. A literature on 'green nudges' has emerged to explore the use of these nudges to promote sustainable decision-making in a range of settings (*e.g.*, Allcott (2011); Goldstein, Griskevicius and Cialdini (2007); Kallbekken and Sælen (2013)).

Changing the default choice in a decision space is a type of nudge that has proven effective in changing behavior (Thaler and Sunstein, 2009). A default refers to a situation in which the decision-maker has to 'opt-out' of an option when making a decision (*e.g.*, a pre-checked box for a subscription to a mailing list). Defaults do not reduce the number of options to choose from or limit individuals' autonomy (*e.g.*, nothing prevents the box from being unchecked), but the default option will be chosen unless the decision-maker explicitly chooses something else. Decision-makers are generally more likely to continue with a pre-selected option than they are to select that option on their own (Dinner et al., 2011). It then follows that policymakers could aim to promote a preferred, prosocial decision by making it the default option for a choice. The classic example of this approach is examined by (Johnson and Goldstein, 2003), which highlights how the number of organ donors can be increased simply by making being an organ donor the default option.

Defaults can be applied to promote environmentally sustainable decisions. In one of the first green default studies, (Löfgren et al., 2012) applied defaults to increase individuals' payments for carbon offsets. Other applications include a lab experiment by (Pichert and Katsikopoulos, 2008) showing defaults increase consumption of renewable energy, (Egebark and Ekström, 2016) reduce paper use by making double-sided printing the default, (Wallander et al., 2023) discuss the application of defaults in agri-environmental conservation programs, and (Zarghamee et al., 2017) increase donations to various environmental and non-environmental charities through a default effect. While not environmentally motivated, (Heydarian et al., 2016) find that indoor lighting decisions can be made more energy efficient through default light settings.

This study examines how default nudges can be applied to indoor thermostat setting decisions. Defaults can be used to conserve energy by both occupants and building managers. Defaults implemented via programmable thermostats have theoretical energy savings of up to 15 percent, though these saving often do not materialize due to factors such as improper thermostat installation, lack of occupant knowledge on how to use temperature schedules, and frequent overrides of the default (Peffer et al. (2013); Brandon et al. (2022)). Despite the obstacles, default temperature schedules have been adopted both in utility policy and in commercial programs as a means to reduce energy use (Sintov and Schultz (2017); Blonz et al. (2023)). For example, Blonz et al. (2023) finds that enrolling homes' smart thermostats in an energy saving program involving defaults creates savings even though users could override the settings at any time.

A highly relevant study to this setting is Brown et al. (2013). Their experiment tests multiple temperature schedules, determining that a default effect did exist (and that lower defaults tend to lead to colder rooms and thus less energy use). However, the effectiveness of the default was highest when only gradual changes to the default were made and making default temperatures too extreme spurred occupant overrides that eliminated savings. Similar experimentation is conducted in Somasundaram, Koch and Lim (2023), which compares the effectiveness of a temperature schedule that gradually adjusts the default to the effectiveness of a temperature schedule that abruptly changes the default. Again, gradual adjustments are found to create the strongest default effect.

1.2 Underlying Psychological Mechanisms of Defaults

An important question for both temperature defaults and defaults in general is what underlying psychological mechanisms create the default effect. An understanding of these mechanisms is essential for the effective design and scaling of default policy. Understanding why a nudge influences behavior creates the possibility of reinforcement via complementary policies that amplify total impact. It is also not a given that a nudge will be equally effective in all settings (Dolan et al., 2012). For example, one explanation for why defaults influence behavior is that decision-makers view defaults as an implied recommendation from the choice architect. This explanation has experimental support in settings such as organ donation (McKenzie, Liersch and Finkelstein, 2006), but has less support in settings such as printer paper use (Egebark and Ekström, 2016) and retirement savings (Blumenstock, Callen and Ghani, 2018).

Nudges have also been known to backfire and actively discourage decisions that the choice architect intended (Mertens et al., 2022) estimates that this occurs for ~15% of choice architecture interventions). For example, Banerjee et al. (2023) finds that the use of defaults actually reduces sustainable food consumption among those who have already taken a sustainability pledge (though this trend dissipates in the long term).

Other unintended consequences of nudges exist in settings such as pesticide use (Chabé-Ferret et al., 2024) and consumption of healthy foods (Diaz-Beltran et al., 2023). In a temperature setting, this could manifest in the form of residents dramatically rejecting the default temperature schedules and setting temperatures to very energy-intensive settings. Such a boomerang effect exists in the more extreme treatments of Brown et al. (2013).

Such twisted results often stem from decision-makers experiencing emotional reactance and seeking to assert their freedom to choose (Banerjee et al., 2023). Heatherly, Baker and Canfield (2023) studies emotional reactance as it pertains to smart thermostats default temperature adjustments, finding that that smart thermostats attempting to set temperatures outside of the user's preferred range induce reactance and increase the likelihood of occupants overriding the default.

Thus, it is important to understand the psychological channels through which defaults operate. A recent literature review of defaults also issues an explicit call for studies that examine how and why different default effects exist in different domains (Jachimowicz et al., 2019). Many explanations for the default effect have been proposed and tested in the default literature. Complicating the issue is that multiple channels can be relevant, and the relevant channels can change depending on the specific setting. The following paragraphs describe the prominent explanations of psychological channels identified in the literature that contribute to the default effect and their applicability to temperature defaults.

The *ease channel* centers around the idea that there are physical and mental costs associated with switching from a default option (Dinner et al., 2011). Physical costs refer to the tasks a decision-maker has to do to change away from the default, while mental costs refer to the mental burden of deciding what change to make. Thus, situations can arise where a decision-maker prefers another option to the default, but the benefits of switching are less than the costs, and thus they stay with the default (Brown et al., 2013). In a similar vein, decision-makers may not fully evaluate all non-default options, instead focusing on whether or not the default is acceptable to them

(Jachimowicz et al., 2019). In the temperature realm, physical costs would involve having to go to the thermostat and select a new temperature. Mental costs would include the decision-making process required to decide what the new temperature should be.

The *endorsement channel* proposes that default options are interpreted as implicit endorsements or recommendations by the choice architect, who presumably has invested thought and research into setting the default to the 'right' option (Dinner et al., 2011). Thus, decision-makers may assume that the choice architect knows best and the default should just be trusted. Alternatively, if the decision-maker is wary of the choice architect (perhaps for political reasons), they may be more inclined to switch away from the default (Jachimowicz et al., 2019). In the temperature setting, this theory would suggest that room occupants interpret the default temperature as a recommendation from the building maintenance or owner, perhaps as a balance between comfort and energy efficiency (or comfort alone).

The *endowment channel* suggests that defaults act as "instant endowments" (Dinner et al., 2011) to decision-makers, creating an endowment effect. Because the default option is perceived as 'owned' by the decision-maker, they value it more than they otherwise would have. This effect is also inherently influenced by reference point/status quo biases, with the most effective defaults perceived as highly reflective of the status quo (Jachimowicz et al., 2019). While relevant in some settings, default temperature does not truly 'endow' occupants with something. It is for this reason that Brown et al. (2013) dismisses it as a possible explanation.

The *present-bias explanation* describes a tendency of present-biased decision-makers to essentially procrastinate on taking actions and making decisions needed to switch away from the default (Blumenstock, Callen and Ghani, 2018). This explanation is particularly relevant when switching away from the default involves immediate costs but delayed benefits (*e.g.*, retirement savings). Applying this theory to temperature could suggest that present-biased room occupants feel discomfort, but cannot be bothered to go adjust the thermostat because it will not result in immediate relief. While this may occur in very short time frames, the role of present-bias in the default effect is likely very low, as the benefits of adjusting room temperature when uncomfortable occur in the short term.

The *salience channel* proposes that the thought of switching away from the default does not occur to the decision-maker, perhaps because the default option draws more attention than the alternatives (Brown et al., 2013). Theoretically, room occupants may not think to change the temperature even when they are cold/hot. Closely related, the *ignorance channel* suggests that decision-makers are not aware that options other than the default exist and/or can be changed to (Blumenstock, Callen and Ghani, 2018). Room occupants may be unaware that they can change the temperature.

The *green guilt explanation* applies specifically to green defaults. This explanation states that decision-makers feel guilt when switching away from green defaults they view as good and moral. This feeling dis-incentivizes switching and increases the default effect (Hedlin and Sunstein, 2016). From a temperature perspective, room occupants that view saving energy as moral may feel guilty switching to more energy-intensive levels.

In addition to the general default explanations, Brown et al. (2013) proposed two temperature-specific explanations as to why their observed default effect existed. First, they suggest that a range of temperatures exists where the decision-maker does not feel any difference. However, once that temperature range is left, discomfort starts to occur and the decision-maker switches away from the default. Second, they propose that the gradual change in temperature default that decision-makers experience actually expands their temperature comfort zone (to a point).

The explanations tested in this study are ease, endorsement, salience, ignorance, and guilt, in addition to the role of gradual temperature adjustment.

Chapter 2

MATERIALS AND METHODS

This study tests the effectiveness of temperature defaults across 566 dorm rooms and 40 communal rooms (lounges, study rooms, etc.) in 5 residence halls at the University of Delaware in 2024 and 2025. The vast majority of dorm rooms were doubles, meaning that there is a room occupant sample size of approximately 1,132 students, most of which are 18 to 20 years of age. A 4-week field experiment session involving 4 treatments and a control was conducted, measuring residents' in-room thermostat use in response to energy-saving temperature schedules that occasionally reset temperatures to a default. Immediately following the temperature default experiment, a survey was distributed to affected residents to test various default explanations and emotional reactance to the study. Finally, a supplementary 3-week session of similar design was conducted the following semester in an attempt to more explicitly leverage the default to create energy savings. All protocols were approved by the University of Delaware's Institutional Review Board (IRBNet No. 2158907-4, See Appendix A1).

2.1 Setting Background

After consultation with UD Facilities, Residence Life and Housing, and the Office of Sustainability, five residence halls were selected for this experiment. All residence halls in this study have identical thermostat systems and were deemed comparable from an energy perspective by the University of Delaware Facilities department (*e.g.*, the buildings had comparable insulation, location, etc.). The HVAC system in these dorms has a lower bound "heating setpoint" and an upper bound "cooling setpoint". If the space temperature in the room is cooler than the heating setpoint, the in-room fan coil unit (FCU) will begin heating the space until temperatures are safely between the setpoints. Similarly, if space temperatures are warmer than the cooling setpoint, the FCU will begin cooling the space. At the beginning of the session, these setpoints were 72°F (heating) and 75°F (cooling). However, every room in this study contains a thermostat that can be adjusted both in-person by occupants and remotely by Facilities. This thermostat can be used to adjust the setpoints by +/-3°F, in 0.5°F increments. This +/-3°F adjustment is called a "user adjustment." If a user adjustment of -3°F was set, for example, the setpoints would become 69°F (heating) and 72°F (cooling). This study tests different default temperature schedules that remotely adjust what the default user adjustment value is.

2.2 2024 Session Description

A two-week pilot, and an additional one-week pilot were conducted in Spring 2024. These pilots offered an opportunity to test planned logistics and gather preliminary data (not included in analysis). The pilots took place in the same rooms as the full session, but with different occupants as it was in a different academic year. Pilot sessions were conducted in both cool and warm outdoor temperatures, but the pilot conducted during warm temperatures was abandoned after a week due to high quantities of student complaints to Facilities about dorm room temperatures. The post-experiment survey was also piloted in Spring 2024 to ensure question clarity and to assess response rate.

The main session was conducted in the Fall 2024 semester. Prior to the this session, a preanalysis plan was completed and published on AsPredicted. Four days before the session began (Thursday), all rooms (including those in the control) had the user adjustment remotely set to 0°F (representing a +0°F adjustment to the original setpoints of 72°F and 75°F). After this initialization, the default temperature schedules rooms experienced for the session depended on their treatment assignment.

As discussed in Chapter 1, previous literature suggests that gradual temperature adjustments create a larger default effect than abrupt adjustments (*e.g.*, Brown et al., 2013; Somasundaram et al., 2023). This study uses a treatment variable to further test this, related to what the default user adjustment value was. The default temperature schedule for gradual treatments began with a default user adjustment of 0°F in Week 1, and then the default user adjustment decreased by 1°F each week until reaching -3°F in the final week. The default temperature schedule for abrupt treatments, on the other hand, used a default user adjustment of -3°F from Week 1.

The other treatment variable is related to how frequently the default temperature schedule resets the user adjustment to the default. The default temperature schedule for high-frequency treatments resets rooms to the default user adjustment every day of the work week (Monday - Friday). Alternatively, the default temperature schedule for low-frequency treatments only resets rooms to the default user adjustment treatments on Tuesday and Thursday. This variable indirectly tests the role of the ease channel for temperature default effects. Assuming that there are greater switching costs associated with the high-frequency treatments relative to the low-frequency treatments, the high-frequency treatments would have a stronger default effect if the ease explanation holds.

The result of this 2x2 treatment design (See Table **??**) is four distinct default temperature schedules. The full schedule across all four treatments can be seen in

	Low Frequency Adjustments	High Frequency Adjustments
Gradual Adjustments	LF-G	HF-G
Abrupt Adjustments	LF-A	HF-A

Table 2.1: Treatment Matrix

Unfortunately, the thermostats used in the residence halls are not smart thermostats. Therefore, default temperature schedules had to be approximated through manual, remote adjustments to the user adjustment. All remote default temperature adjustments were applied by Facilities at approximately 6:00am following the treatment schedules described above. Residents were not made aware of these adjustments or the study in general until after the session was completed.

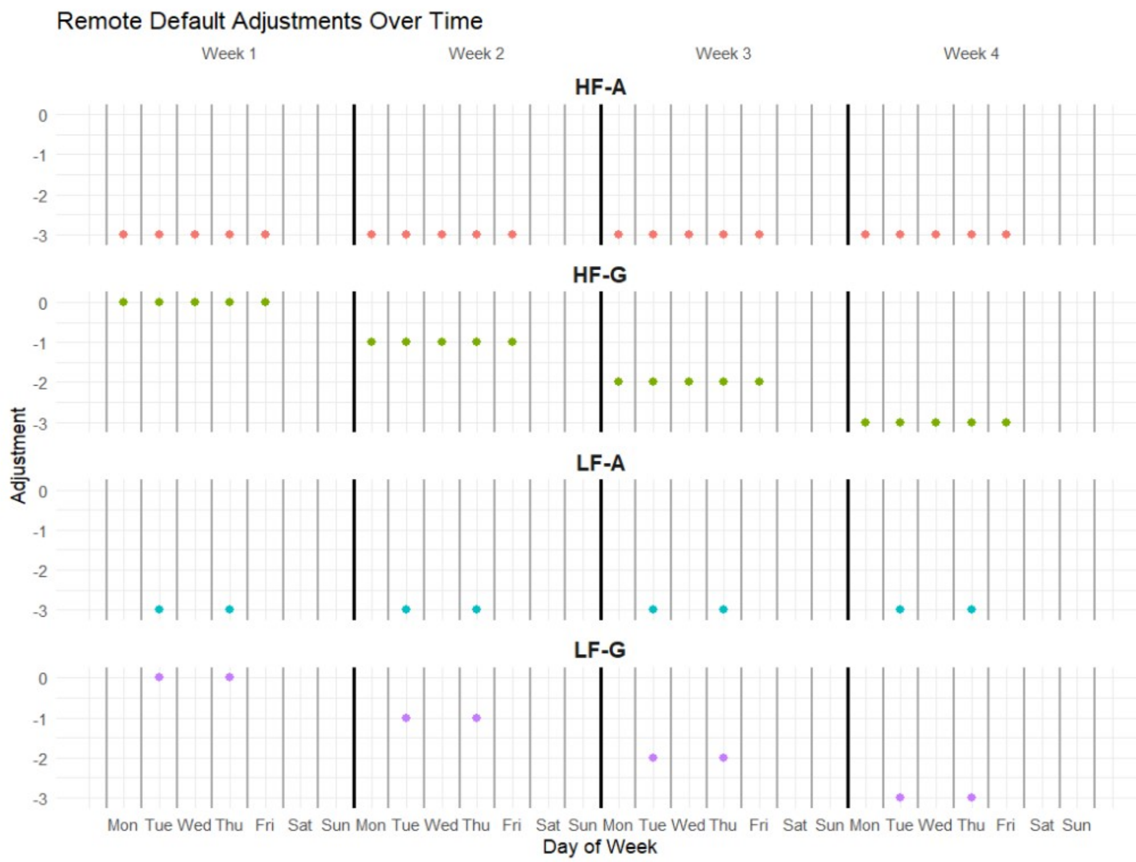

Figure 2.1: Remote Default Adjustments Schedules

Rooms were assigned to treatments in a semi-random matter. Each residence hall has a pre-existing "listview" (essentially a spreadsheet) that is used by Facilities to make adjustments to large numbers of rooms with fewer commands. The order of the rooms within the listview is random. For the sake of administrative ease and accuracy of remote adjustments, treatment assignment was done by splitting the listviews into 5 continuous groups (4 treatments + control). Small nuances in how these listviews work resulted in slight differences in treatment sample size. Nevertheless, due to the random nature of room placement in listviews, there is no reason to think that any systematic biases exist from this treatment assignment method.

2.3 Survey

Following the session, an anonymous survey was sent out to all residents in the study. The full survey can be seen in Appendix A.2. To encourage responses, respondents were offered the opportunity to enter an Amazon e-gift card raffle upon completion. This survey informed residents of the session, gauged initial reactions, explored general awareness and knowledge of the dorm's HVAC system, and tested the role of the relevant default effect psychological channels discussed above. The survey also contained an optional question that allowed participants to share their dorm room number. This allowed a segment of survey responses to be linked to room thermostat data.

2.4 2025 Session

As will be discussed in more detail in the Results section, the 2024 session identified a default effect that resulted in cooler space temperatures. However, the impact this default effect had on energy consumption is unclear for two reasons. First, Facilities had to develop an equation to calculate individual FCU energy use, and this equation was not fully developed until after the 2024 session concluded. Upon full development, it was discovered that a key variable to the calculation was not being collected, meaning only vague approximations could be made. Second, a good number of rooms experienced space temperatures near the top end of the setpoint range. This meant that remote temperature schedules that lowered the user adjustment value often moved the cooling setpoint below the space temperature, triggering the FCU to expend energy to cool the space. While the default temperature schedules plausibly reduced heating energy use, those savings could conceivably have been offset by increased cooling energy use.

An underlying issue is that lowering the heating setpoint also lowers the cooling setpoint, which can increase the use of cooling energy. A potential way to address this could involve widening the setpoint range to 69°F (heating) and 75°F (cooling), and remotely adjusting the user adjustment to 0 to reinforce a cooling setpoint that would not trigger the FCU. This approach retains a lower heating setpoint of 69°F (which should save energy as the FCU system can be off more of the time) without also lowering the cooling setpoint and turning on the AC.

To test this approach, a supplemental session was conducted in February 2025. While similar to the 2024 session, there were some design changes applied to the 2025 session. On Day 1, all of the rooms' thermostats were remotely set to an adjustment of 0 and a default adjustment schedule followed. However, there were only two treatments in this session (See Table 2.2). Treatment 1 experienced the widened setpoint range, but experienced no default temperature schedule. Treatment 2 also experienced the widened setpoint range, but additionally experienced a default temperature schedule that set the user adjustment value to 0 once a week on Friday. The same set of rooms were used and, barring a possible small number of occupant changes, the residents remained the same as well. While many residents were aware of the Fall 2024 session by the time the 2025 Spring session took place, they were not informed that a new session was being conducted.

Table 2.2: 2025 Treatment Matrix

	Status Quo Setpoints	Widened Setpoints
Remote Adjustments	Not Tested	T1
No Remote Adjustments	Control	T2

Treatment assignment in the 2025 session was applied more coarsely at the request of Facilities, again with attention to limiting their administrative burden. Three of the five buildings represented the control, and Treatment 1 and Treatment 2 were assigned by splitting the largest residence hall in half (with a small supplement from another building to balance sample sizes across the treatments).

2.5 Data Collection

Data were collected through Continuum, the building management software used for certain buildings at the university. For each room observed in this study, a data sheet exists that provides data on the room's space temperature, user adjustment, and heating/cooling mode. Data were collected hourly for each room from October 4 to November 16, 2024. The data points collected before October 7 represents the period of time following the initialization of rooms at a user adjustment of 0. The data collected after November 3 (~2 weeks) is used to examine possible persistence of the default effect on user adjustment values.

In the 2025 session, data were collected from February 3 to March 7, 2025. The data collected before March 7 (~1 week) was used to establish a baseline for rooms, and the data collected after Feb 28 (~1 week) was used to examine possible persistence of the default effect. Data were again collected hourly and, in addition to the data points mentioned above, additional data on the energy use of each FCU were also collected.

2.6 Hypotheses

Three specific hypotheses were tested in this study.

Hypothesis 1: A default effect will exist across all treatments, resulting in lower average user adjustment values relative to the control.

Hypothesis 2: Gradual treatments will experience lower average user adjustment values than abrupt treatments.

Hypothesis 3 - High-frequency treatments will experience lower average user adjustments than low-frequency treatments.

2.7 Empirical Strategy

We test for the presence and strength of a default effect by examining how adjustments to temperature settings differed in each treatment and the control. The main outcome variable is each dorm room's user adjustment (space temperature was also examined, but is a less reliable measure of behavior as room temperature is only indirectly influenced by residents' decisions). A strong default effect is signified by observed user adjustment values being very similar or identical to the default user adjustment value. A secondary outcome variable is the average number of manual adjustments made to thermostats. Using this metric, a strong default effect is signified if there are no or few manual adjustments to thermostat settings.

Drawing from Brown et al. (2013)'s difference-in-differences approach, the average treatment effect for each treatment in each week can be approximated with the following equation:

$$ATE_{wt} = (\overline{S}_{wt} - \overline{S}_{wC}) - (\overline{S}_{0t} - \overline{S}_{0C})$$

In this approximation, S represents the average user adjustment for the specified Week w (with 0 representing the baseline) and Treatment t (with C representing the Control). The full regression equation to estimate treatment effects is as follows:

$$S_{ih} = \beta_0 + \sum_{w=1}^{6} \beta_w d_{wh} + \sum_{t=1}^{4} \gamma_t q_{ti} + \sum_{w=1}^{6} \sum_{t=1}^{4} ATE_{wt}(d_{wh} \times q_{ti}) + \epsilon_{ih}$$

This model estimates how the treatments influence user adjustments (S) for any given room i at hour h. Both d and q are indicator variables for week and treatment, respectively. To explore the impact of treatment (and week), models with and without treatment-week interactions are estimated. Standard errors are clustered at the room level. Both random and fixed effect models are estimated to assess the robustness of the results to alternative model specifications. Finally, two Tobit models (with and without interactions) are used to account for the censoring of user adjustment values at -3 and 3.

For the 2025 session, the amount of energy the FCUs in this study use can be approximated by the following equation

$$BTU/hr = GPM * 500 * \Delta T$$

With GPM representing the gallons of water per minute that the FCU is using, Delta T representing the difference between the temperature of water entering and leaving the building, and 500 being derived from the standard heat transfer equation (using water's standard values of 1 Btu/lb/°F for specific heat capacity and 8.34 lb/gal for density, see Appendix A.5 for derivation).

GPM is calculated through the following equation

$$GPM = \frac{VLV\%}{100} * GPM_{Max}$$

With VLV representing the percent open that the FCU's valve is (0% to 100%) and GPM Max representing the maximum water flow the FCU can have. VLV was recorded hourly on the data collection sheets. All dorm rooms in the study use FCU type C, which has a GPM Max of 1.5.

The value of Delta T depends on whether the FCU is in heating or cooling mode. Facilities has approved an estimate of Delta T = 5 for cooling mode and Delta T = 10 for heating mode. Thus, in heating mode the FCU energy consumption is given by:

$$BTU/hr = (\frac{VLV}{100} * 1.5) * 500 * 10 = VLV * 75$$

In cooling mode, the FCU energy consumption is given by:

$$BTU/hr = (\frac{VLV}{100} * 1.5) * 500 * 5 = VLV * 37.5$$

The cost of energy was provided by Facilities: \$4.2 per MMBTU for heating mode and \$5 per MMBTU for cooling mode.

Chapter 3

RESULTS & DISCUSSION

3.1 Regression Results

General descriptive statistics are presented for rooms' user adjustments (Table 3.1 and Figure 3.1), space temperature (Table 3.6 and Figure 3.2), and manual adjustments (Table 3.2). Results from the regression models are given in Table 3.30 and Table 3.31. Results from the fixed and random effects models are identical to 8 or more decimal places. Results from the Tobit model differ some in value, though the estimated values' sign and significance match the other models. While it is likely that some room temperatures would have been adjusted below -3 if possible, the Tobit results are also likely influenced by the negative skew of the data: 318,983 values are censored at -3 whereas only 2,686 values are censored at 3. The Tobit model has underlying assumptions of normality which are not fully met by this dataset (McBee, 2010). This limits the reliability of interpretations drawn only from the Tobit models.

Table 3.29 shows the ATEs estimated with the regression model, along with the percentage of rooms in each treatment that remained at the default user adjustment value for 100, 90, and 50 percent of the time.

3.1.1 Default Effect Evidence

The more time the user adjustment remains at the default settings, the stronger the default effect. This can be directly measured week-by-week by comparing the observed average user adjustment value and the default user adjustment value. Time spent at the default can also be assessed by examining the number of manual adjustments made, with 0 manual adjustments representing 100 percent of time being spent at the default. It is much more challenging to gauge the default effect with space temperature. Residents only indirectly impact space temperature (especially in the short term), and many confounding variables exist. The relevance of space temperature data will be discussed in Section 3.3.5.

As shown in Figure 3.1 and Tables 3.1 and 3.2, observed data of both user adjustment values and manual adjustments are similar to what would be associated with a default effect. The observed user adjustment values are consistently near the default values throughout the entire session, despite default values varying significantly across weeks and treatments. Manual adjustments are uncommon, with all treatments averaging ~1 adjustment per week per room or less. Furthermore, results shown in Table 3.30 show clear evidence of a default effect. All coefficients are statistically significant ($p < 0.01$), with the exception of treatment coefficients in the random effects model with interactions. This is an expected result, as the default setting for Treatment LF-G and Treatment HF-G varied by week, and as all treatments and the control were set to the same default value in Week 0. Summarizing the full session in one value makes the early weeks' and later weeks' defaults cancel out, to an extent.

3.1.2 Persistence of Default Effect

In all treatments, there is evidence that the default effect persists beyond the end of the default temperature schedules. All treatment-week coefficients are statistically significant even after the session concluded ($p < 0.01$), indicating that the average user adjustment and space temperature are still cooler than the control in weeks 5 and 6. Compared to Week 4 (Treatment LF-G: -0.975, Treatment HF-G: -1.467, Treatment LF-A: -1.034, Treatment HF-A: -0.992), the average user adjustment coefficients in treatments were warmer in both Week 5 (Treatment LF-G: -0.901, Treatment HF-G: -1.112 , Treatment LF-A: -0.895 , Treatment HF-A: -0.838) and Week 6 (-0.85°F; Treatment LF-G: -0.841, Treatment HF-G: -1.111, Treatment LF-A: -0.871, Treatment HF-A: -0.807). This diminishing but present persistence can also be seen in Table 3.29,

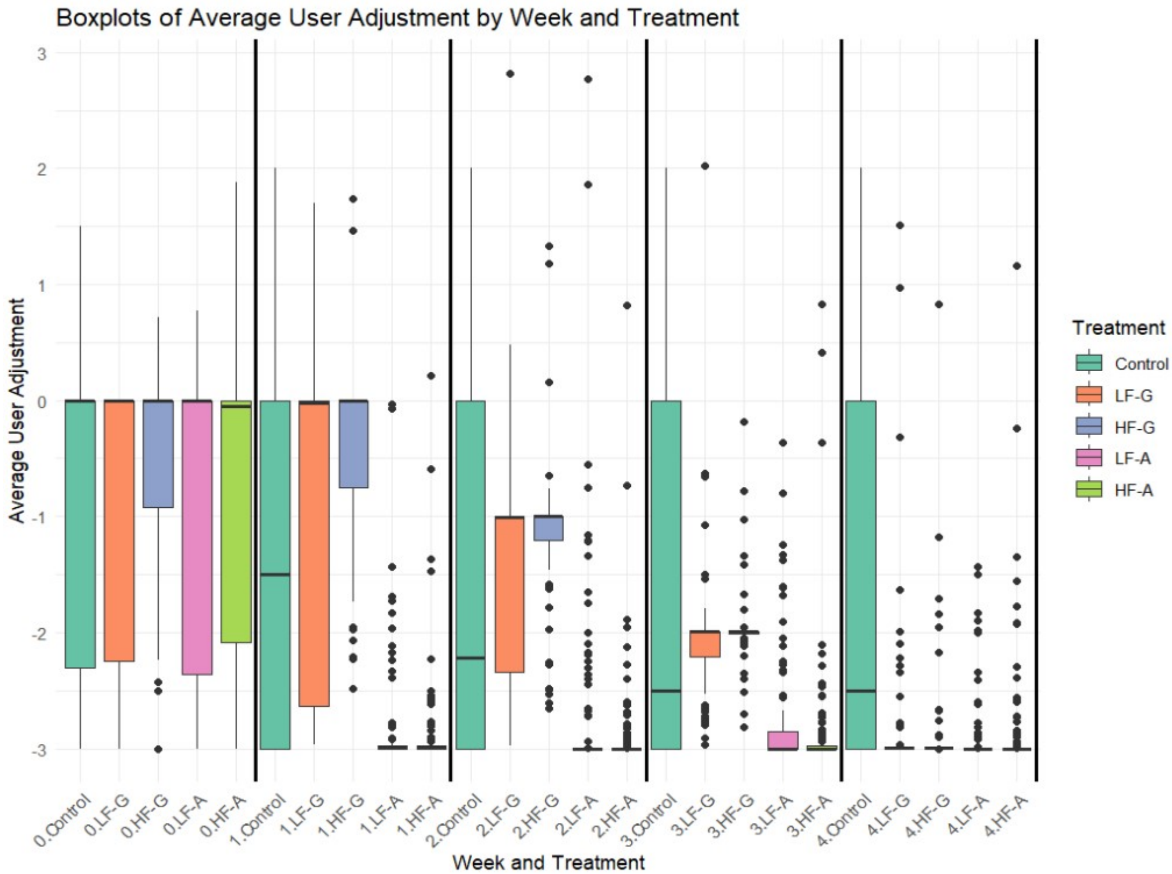

Figure 3.1: Boxplots of Average User Adjustment by Week and Treatment

where the number of rooms at the default remains relatively high in Weeks 5 and 6, but are lower than they were in Week 4.

Table 3.1: User Adjustments

Week, Treatment	Observed User Adjustment (Avg.)	Default User Adjustment
Week 0, LF-G	-1.04	0.00
Week 1, LF-G	-1.01	0.00
Week 2, LF-G	-1.58	-1.00
Week 3, LF-G	-2.08	-2.00
Week 4, LF-G	-2.86	-3.00
Week 5, LF-G	-2.85	-3.00
Week 6, LF-G	-2.71	-3.00
Week 0, HF-G	-0.59	0.00
Week 1, HF-G	-0.41	0.00
Week 2, HF-G	-1.13	-1.00
Week 3, HF-G	-1.99	-2.00
Week 4, HF-G	-2.91	-3.00
Week 5, HF-G	-2.61	-3.00
Week 6, HF-G	-2.53	-3.00
Week 0, LF-A	-1.03	0.00
Week 1, LF-A	-2.83	-3.00
Week 2, LF-A	-2.67	-3.00
Week 3, LF-A	-2.75	-3.00
Week 4, LF-A	-2.91	-3.00
Week 5, LF-A	-2.83	-3.00
Week 6, LF-A	-2.73	-3.00
Week 0, HF-A	-1.00	0.00
Week 1, HF-A	-2.86	-3.00
Week 2, HF-A	-2.89	-3.00
Week 3, HF-A	-2.84	-3.00
Week 4, HF-A	-2.84	-3.00
Week 5, HF-A	-2.74	-3.00
Week 6, HF-A	-2.64	-3.00

Table 3.2: Average Number of Manual Adjustments

Treatment	Week 0	Week 1	Week 2	Week 3	Week 4	Session Manual Adjustments	Week 5	Week 6
Control	0.30	0.82	0.39	0.40	0.39	2.00	0.54	0.47
LF-G	0.29	1.26	0.72	0.69	0.39	3.06	0.27	0.24
HF-G	0.28	1.65	1.41	0.88	0.43	4.38	0.38	0.38
LF-A	0.40	1.02	0.51	0.31	0.41	2.25	0.23	0.33
HF-A	0.51	1.22	0.76	0.85	1.00	3.84	0.54	0.46

3.1.3 Heterogeneity

An interesting finding can be seen in Table 3.29 in the control group. The difference between the percentage of rooms at the default user adjustment 50+ percent of the time and 100 percent of the time is very low. These numbers suggest heterogeneity in the use of thermostats, as about a quarter of rooms in the control (23.68 percent) experienced no changes to thermostat settings the whole session but also over 60 percent of rooms in the control experienced a change to thermostat setting before Week 1 even began. Heterogeneity existed in all rooms, not just the control. The average room in a treatment only experienced 3.38 manual adjustments during the session. This average contains two distinct groups, though: those who made any adjustments ("Frequent Adjusters") and those who did not ("Infrequent Adjusters"). Of the 566 rooms, 67 percent (378) made at least one manual adjustment. Among these 378 rooms, the average number of manual adjustments across the session was 4.70, compared to the 0 adjustments made by the other 188 rooms (Table 3.3). As can be seen in Table 3.4, Frequent Adjusters in Treatment LF-G and Treatment HF-G tended to maintain a cooler user adjustment in the early weeks, while frequent adjusters in Treatment LF-A and Treatment HF-A maintained a user adjustment about 0.25˚F warmer than the infrequent adjusters.

Table 3.3: Manual Adjustments by Frequent Adjusters

LF-G Manual Adjustments	HF-G Manual Adjustments	LF-A Manual Adjustments	HF-A Manual Adjustments
4.29	6.20	2.85	5.44

Table 3.4: Heterogeneity in User Adjustment Values

Treatment	Week.1.I	Week.1.F	Week.2.I	Week.2.F	Week.3.I	Week.3.F	Week.4.I	Week.4.F	Diff
Control	-1.42	-1.45	-1.42	-1.76	-1.42	-1.96	-1.42	-2.00	-0.37
LF-G	0.00	-1.40	-1.00	-1.80	-1.99	-2.11	-2.99	-2.81	-0.54
HF-G	0.00	-0.69	-0.99	-1.23	-1.99	-1.99	-2.99	-2.85	-0.19
LF-A	-3.00	-2.78	-3.00	-2.57	-3.00	-2.67	-3.00	-2.89	0.27
HF-A	-3.00	-2.80	-3.00	-2.84	-3.00	-2.77	-3.00	-2.77	0.21

3.1.4 Control Group Trends

A complication of the data is that residents have a tendency to choose cooler user adjustments regardless of whether there is a default temperature adjustment schedule promoting cooler settings. As can be seen in Figure 3.1 and Table 3.5, the control quickly settles into an average user adjustment of around -1.7°F after the initialization at 0°F in Week 0. This is also illustrated in the week effects of the regression models. By far the largest drop in user adjustment occurred from Week 0 to Week 1, dropping -0.853°F. This is reflective of the large number of control rooms leaving the default. User adjustment then continued to drop by about 0.25°F to 0.35°F a week, settling at -1.701°F in the last week of the session.

Table 3.5: Average User Adjustment - Control

Treatment	Average User Adjustment
Week 0, Control	-0.86
Week 1, Control	-1.44
Week 2, Control	-1.59
Week 3, Control	-1.69
Week 4, Control	-1.71
Week 5, Control	-1.77
Week 6, Control	-1.69

This downward movement of the control makes it more challenging to separate the default effect from the apparent tendency of residents to select cooler temperatures on their own. That being said, a general observation indicating a default effect is that, when all treatments were set to -3°F in Week 4, all treatments experienced a lower user adjustment than the control. Additionally, the cooling of Treatments 1 and 2 throughout the session did not occur at the same rate as the control. Econometric analysis shows that treatment coefficients (model without interaction) and treatment-week coefficients (model with interaction) are statistically significant ($p < 0.01$) despite the movement of the control. While at a glance the movement of the control may make the default effect appear more pronounced than it may actually be, it does not explain the findings.

3.1.5 Role of Space Temperature and Outdoor Air Temperatures

As previously discussed, the user adjustment influences space temperature by adjusting the setpoints which control when the FCU turns on. In theory, when the outdoor air temperatures are cooler than the heating setpoint (as they were during this session), the space temperature of the room should gradually decline to the heating setpoint. However, other factors such as time spent in room, frequency of hosting guests, and the sex of the residents (males produce more body heat) can affect this progression. Plug in heaters would also be a confounding factor, but these are rarely used per survey data (less than 4 percent of respondents indicating using one). If the user adjustment has too indirect an impact on space temperature, this would call into question the validity of any findings. After all, residents' comfort is determined by the actual temperature of the room, not what the setting is.

There is evidence that factors other than the default user adjustment value affect space temperatures, as can be seen in Figure 3.2 and Table 3.6. The majority of rooms in all treatments and the control seem to 'hit a wall' at around 71°F or 71.5°F and cool much slower if at all afterwards, even though the setpoint range would allow temperatures as cool as 69°F. In part because of this, some of the coefficients in Table 3.31 are less significant than the regression results from the user adjustment regression. This is a reflection of the indirect influence of user adjustment on space temperature. Despite this, all treatment-week coefficients are statistically significant ($p < 0.01$), indicating that treatments did have an impact on space temperature. While the connection is indirect, rooms set to lower default user adjustment values do appear to experience cooler space temperatures. This indicates that findings can indeed be attributed to the default and not variance in space temperature caused by outside factors.

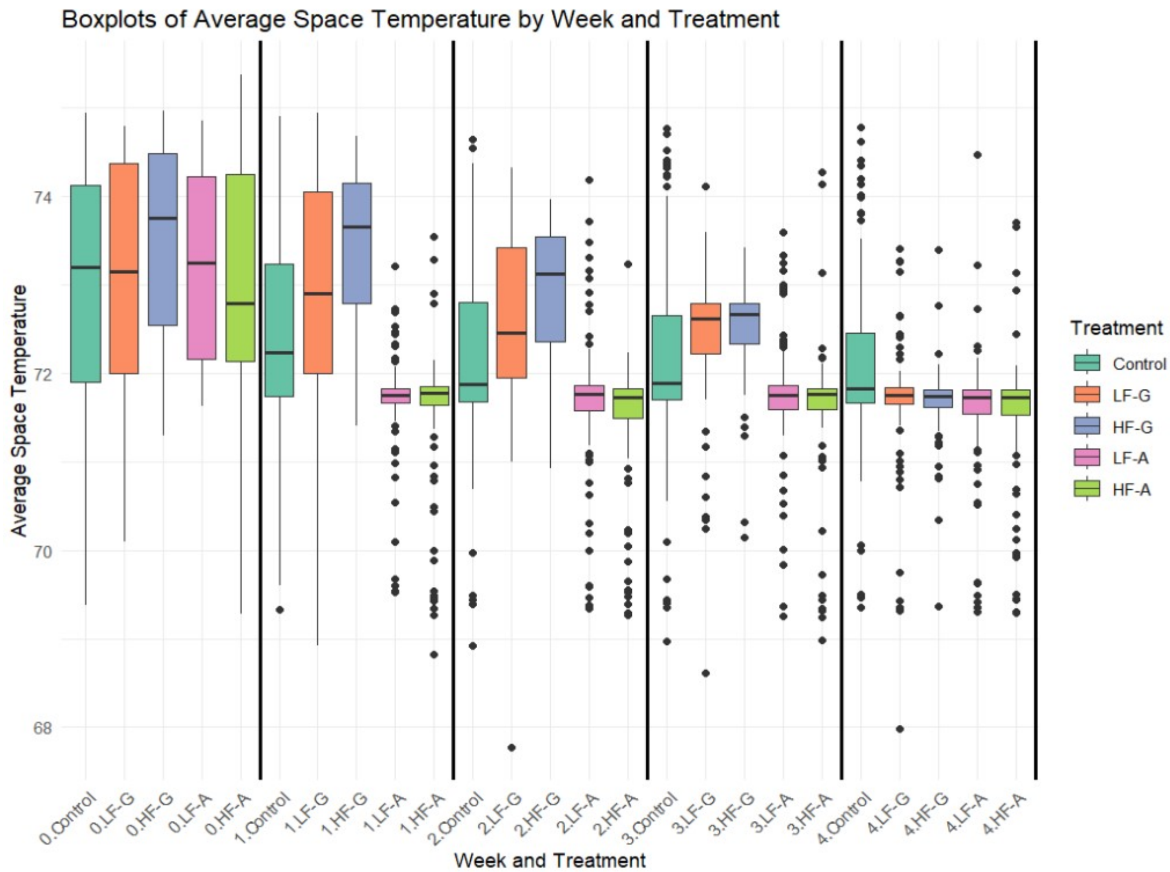

Figure 3.2: Boxplots of Space Temperature Average by Week and Treatment

Another factor outside of the default that could influence thermostat decisions is the outdoor air temperature (Yan et al., 2016). As can be seen in Table 3.7, the average outdoor air temperature during weeks 1 to 4 was 56.8°F, and the average was 56.6°F across all weeks (0 to 6). As shown in Figure 3.3, changes in outdoor temperature do not appear to impact space temperatures or user adjustments much if at all, again indicating confidence in the findings being attributable to the defaults.

Table 3.6: Space Temperatures

Week-Treatment	Observed Space Temperature
Week 0, LF-G	73.16
Week 1, LF-G	73.03
Week 2, LF-G	72.58
Week 3, LF-G	72.39
Week 4, LF-G	71.65
Week 5, LF-G	71.64
Week 6, LF-G	71.61
Week 0, HF-G	73.48
Week 1, HF-G	73.45
Week 2, HF-G	72.89
Week 3, HF-G	72.49
Week 4, HF-G	71.65
Week 5, HF-G	71.77
Week 6, HF-G	71.68
Week 0, LF-A	73.11
Week 1, LF-A	71.67
Week 2, LF-A	71.66
Week 3, LF-A	71.72
Week 4, LF-A	71.54
Week 5, LF-A	71.59
Week 6, LF-A	71.41
Week 0, HF-A	73.07
Week 1, HF-A	71.57
Week 2, HF-A	71.48
Week 3, HF-A	71.59
Week 4, HF-A	71.53
Week 5, HF-A	71.60
Week 6, HF-A	71.50

Table 3.7: Average Outdoor Air Temperatures

Week 0	Week 1	Week 2	Week 3	Week 4	Session	Week 5	Week 6	Total
65.05	60.01	53.17	57.94	56.85	56.83	58.97	49.40	56.61

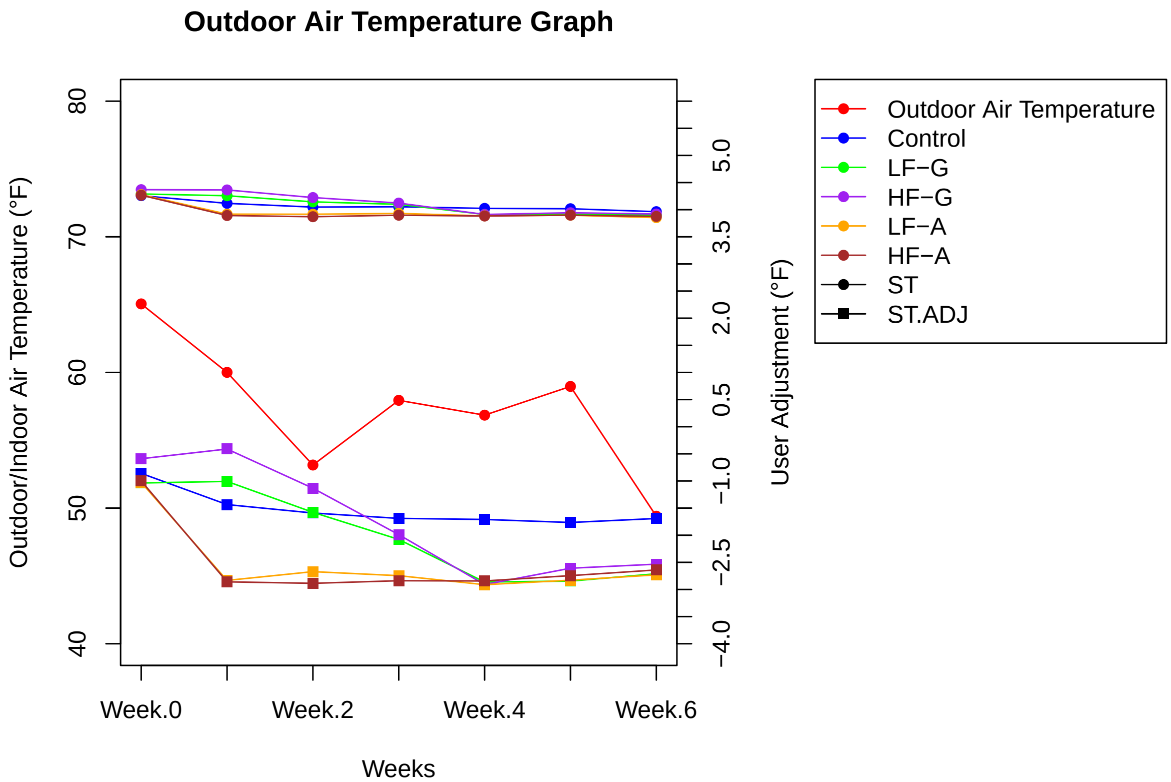

Figure 3.3: Outdoor and Indoor Air Temperatures

3.2 Hypothesis Evaluation

3.2.1 H1:A default effect will exist across all treatments, resulting in lower average user adjustment values relative to the control

As discussed earlier, the ATEs and low number of manual adjustments provide strong support for the existence of a default effect. Treatment has a statistically significant ($p < 0.01$) impact on user adjustment when no interactions are modeled, and enrollment in the abrupt treatments creates a statistically significant ($p < 0.01$) reduction in average space temperature by a bit more than 0.5°F compared to the control. Assignment to the gradual treatments does not create a statistically significant effect ($p > 0.05$), which is likely due to a combination of a) the indirect relationship of space temperature and user adjustment and b) the limited use of session-long treatment effect coefficients for the gradual treatments (whose defaults change week to week). This lack of significance is not overly concerning because, as was discussed, treatment-week effects on space temperature are statistically significant ($p < 0.01$).

When only examining the treatment ATEs for user adjustment from the random effect model with no interactions, the direction of this hypothesis is supported as well. Relative to the control, user adjustments in Treatment LF-G were 0.497°F cooler, user adjustments in Treatment HF-G were 0.234°F cooler, user adjustments in Treatment LF-A were 1.092°F cooler, and user adjustments in Treatment HF-A were 1.109°F cooler. The Tobit model without interaction shows even more pronounced negative ATEs. However, this hypothesis incorrectly assumes that residents' preferred temperature is warmer than the gradual treatments throughout the entire session. This was not the case, as demonstrated by the control's average user adjustment of about -1.7°F. Due to the rapid decline of the control between Week 0 and Week 2, the gradual adjustments actually had positive coefficients in Week 1 (0.604 and 0.753) and Week 2 (0.190 and 0.187). In Week 3 the Tobit model shows Treatment LF-G with a positive coefficient of 0.403 and Treatment HF-G with a coefficient of 0.013 ($p > 0.1$, however). Though the data support this hypothesis in the aggregate, support for this hypothesis varies week-to-week.

3.2.2 H2: Gradual treatments will experience lower average user adjustment values than abrupt treatments

As discussed in H1, in the random effects model gradual treatments began with positive coefficients in Week 1 (0.604 and 0.753) and Week 2 (0.190 and 0.187) but end with negative coefficients in Week 3 (-0.210 and -0.567) and Week 4 (-0.975 and -1.467). Treatment LF-A (-1.229, -0.912, -0.888, -1.034) and Treatment HF-A (-1.282, -1.154, -1.006, -0.992) both remained fairly stable across all weeks, though the coolest average of both Treatments occurred in Week 1. This is likely because the abrupt treatments were unable to get any cooler, whereas the control crept downwards. These results do not support this hypothesis.

3.2.3 H3: High-frequency treatments will experience lower average user adjustments than low-frequency treatments

The frequency of remote user adjustment defaults did not seem to have a large impact on the average user adjustment value, in large part because of how strong the default effect was (particularly for cooler default values). It may not matter much how frequently the default is reset to -3, because residents are not switching away frequently or at all.

However, evidence suggests that the frequency remote user adjustment defaults may impact the average user adjustment value of rooms that experience a greater-than-average number of manual adjustments. As can be seen in the ATE table (Table 3.29), Treatment HF-G had more rooms spending at least 50 percent of the time at the default than Treatment LF-G did, as did Treatment HF-A over Treatment LF-A. This makes intuitive sense, as it would take more work to stay off the default in high-frequency treatments. Another possible impact of the frequency is that the high frequency treatments had the most manual adjustments, both in general and among Frequent Adjusters.

3.3 Survey Data

3.3.1 Survey Overview

Following the session and two-week persistence observation, a survey was sent out to all students who lived in a residence hall that was part of the study (1,147 total students). A total of 235 fully completed responses were received, creating a response rate of 20 percent. Among these, a total of 231 dorm rooms (41% of all rooms) were explicitly represented (34 rooms had two respondents, 2 rooms had three respondents, and 4 respondents did not share their room). Responses were received from residents of all five residence halls at a rate more or less proportional to the student distribution between the buildings. Respondents skewed female (63 percent). Survey participation was incentivized through the raffling of multiple Amazon e-gift cards.

3.3.2 Possible Spillover Effects from Pilot

A possible confounding of results would occur if a large subsection of the residents suspected that the session was happening, perhaps because they learned about the pilot. To examine this, survey respondents were asked if they either knew of or participated in the Spring 2024 pilot (Table 3.8. 17 respondents reported being a part of the pilot (Resident Assistants, etc.), with another 6 saying they were aware of it despite not participating. This amounts to only 9.3 percent of respondents having any sort of knowledge about the study while data collection was ongoing. Even among this 9.3 percent, there was still no reason to think the pilot was being repeated. While these residents could have possibly noticed the default temperature adjustment schedule undoing their settings, the most they could have done is wonder if a session like the pilot was running again. This, combined with the relatively small number of respondents with any awareness of the pilot, seem to suggest that any spillover is minimal.

Table 3.8: Last Spring, were you informed of being involved in a similar study?

Treatment	No	Yes	No, but I knew a similar study took place last Spring	Not sure
LF-G	28 (84.8%)	4 (12.1%)	0 (0%)	1 (3%)
HF-G	38 (84.4%)	3 (6.7%)	0 (0%)	4 (8.9%)
LF-A	39 (79.6%)	3 (6.1%)	1 (2%)	6 (12.2%)
HF-A	34 (85%)	2 (5%)	2 (5%)	2 (5%)
Control	51 (82.3%)	4 (6.5%)	1 (1.6%)	6 (9.7%)
Aggregate	193 (82.1%)	17 (7.2%)	5 (2.1%)	20 (8.5%)

3.3.3 Evidence for Default Psychological Channels

In an attempt to tease out the underlying psychological channels used by the default effect, respondents were asked a series of questions that corresponded to the various explanations posed in the literature, both in regards to their dorm room and their residence hall's communal spaces.

All channels explicitly tested found some level of support. However, the ease and ignorance channels appear the most explanatory, in addition to a social considerations component. That being said, it remains possible if not probable that the channels are heterogeneous in explanatory power. For instance, it is highly plausible that among highly eco-conscious students (perhaps those in environmental programs) the green guilt explanation plays an outsized role compared to the average student.

3.3.3.1 Ease

The ease explanation proposes that the default effect is a result of the mental and physical costs of adjusting the thermostat outweighing the perceived benefits of temperature adjustment, or at a minimum alternative actions (*e.g.*, putting on/taking off a sweatshirt). Respondents were asked how much more frequently they would adjust the temperature if it were easier to do so (*e.g.*, an app on their phone). Additionally, residents were asked what influenced their decision to adjust the temperature other than personal comfort. One of the options they could select was effort required to change the temperature.

Survey results supported this explanation, particularly for dorm rooms (Table 3.9. 82 percent indicated that they would adjust the temperature of their dorm room more frequently if it were easier to do so, with 35 percent indicating that they would do so significantly more frequently. Additionally, 21 percent said that the effort required to change the temperature factored into their decision-making process surrounding temperature adjustment for their dorm room (Table 3.16).

Table 3.9: If it were easier to adjust the temperature of your dorm room, do you think you would adjust the temperature more frequently?

Treatment	A little bit more frequently	Significantly more frequently	I would not adjust temperatures more
LF-G	18 (54.5%)	11 (33.3%)	4 (12.1%)
HF-G	20 (44.4%)	15 (33.3%)	10 (22.2%)
LF-A	22 (44.9%)	18 (36.7%)	9 (18.4%)
HF-A	26 (65%)	10 (25%)	4 (10%)
Control	26 (41.9%)	22 (35.5%)	14 (22.6%)
Aggregate	116 (49.4%)	78 (33.2%)	41 (17.4%)

The survey provided less support for this explanation when it comes to communal rooms, though still some (Table 3.10. 44 percent (38 percentage points less than dorm rooms) indicated that they would adjust the temperature of their communal room more frequently if it were easier to do so, with 14 percent indicating that they would do so significantly more frequently. 18 percent (3 percentage points less) said that the effort required to change the temperature factored into their decision-making process surrounding temperature adjustment for communal rooms (Table 3.17).

Table 3.10: If it were easier to adjust the temperature of of communal rooms in your residence hall, do you think you would adjust the temperature more frequently?

Treatment	A little bit more frequently	Significantly more frequently	I would not adjust temperatures more
LF-G	14 (42.4%)	1 (3%)	18 (54.5%)
HF-G	15 (33.3%)	9 (20%)	21 (46.7%)
LF-A	14 (28.6%)	8 (16.3%)	27 (55.1%)
HF-A	10 (25%)	3 (7.5%)	27 (67.5%)
Control	15 (24.2%)	13 (21%)	34 (54.8%)
Aggregate	70 (29.8%)	34 (14.5%)	131 (55.7%)

3.3.3.2 Endorsement

The endorsement explanation suggests that the default effect is a result of the perception that someone, probably an authority figure, set the room temperature to that level for a reason (and residents are willing to go along with that implicit recommendation). Respondents were explicitly asked if they thought of the dorm room and communal room default temperatures as a recommendation of what temperature to keep the room at.

The endorsement explanation received moderate support from the survey, with 54 percent (for dorm rooms) and 59 percent (for communal rooms) of respondents agreeing that they viewed the default set temperature of the room thermostat as the recommended temperature for the room (Tables 3.11 and 3.12).

To further examine this channel, a small analysis was done comparing the number of manual adjustments done by rooms who responded affirmatively to the endorsement question vs those who responded neutrally or negatively. If this channel is

Table 3.11: How much do you agree with the following statement: I view the default set temperature of my dorm room thermostat as the recommended temperature for my room

Treatment	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
LF-G	9 (27.3%)	12 (36.4%)	2 (6.1%)	8 (24.2%)	2 (6.1%)
HF-G	6 (13.3%)	17 (37.8%)	12 (26.7%)	7 (15.6%)	3 (6.7%)
LF-A	3 (6.1%)	22 (44.9%)	10 (20.4%)	8 (16.3%)	6 (12.2%)
HF-A	5 (12.5%)	12 (30%)	9 (22.5%)	8 (20%)	6 (15%)
Control	16 (25.8%)	20 (32.3%)	8 (12.9%)	15 (24.2%)	3 (4.8%)
Aggregate	41 (17.4%)	85 (36.2%)	43 (18.3%)	46 (19.6%)	20 (8.5%)

Table 3.12: How much do you agree with the following statement: I viewed the original temperature of the communal rooms' thermostats as the recommended temperature for the room

Treatment	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
LF-G	5 (15.2%)	9 (27.3%)	14 (42.4%)	5 (15.2%)	0 (0%)
HF-G	11 (24.4%)	17 (37.8%)	14 (31.1%)	1 (2.2%)	2 (4.4%)
LF-A	12 (24.5%)	18 (36.7%)	12 (24.5%)	4 (8.2%)	3 (6.1%)
HF-A	10 (25%)	11 (27.5%)	13 (32.5%)	5 (12.5%)	1 (2.5%)
Control	19 (30.6%)	24 (38.7%)	14 (22.6%)	5 (8.1%)	0 (0%)
Aggregate	59 (25.1%)	80 (34%)	70 (29.8%)	20 (8.5%)	6 (2.6%)

explanatory, rooms who agreed ought to experience a lower average number of adjustments. Of course, it could always be the case that observed adjustments were done by roommates rather than respondents. 113 rooms responded affirmatively, with an average number of 3.3 manual adjustments during the session. 102 rooms responded non-affirmatively, averaging a slightly higher 3.7 manual adjustments during the session. This further supports the idea that implicit endorsement has a lesser impact on thermostat decisions.

3.3.3.3 Salience

The salience explanation of the default effect is that people do not think to change the temperature even when they are hot/cold. No direct testing of this explanation occurred, though the large percentage of respondents listing multiple factors that go into their temperature decision-making suggests that residents are consciously thinking about temperature adjustments (tables 3.16 and 3.17).

An indirect test of this mechanism was conducted by examining temperate data of a room immediately following the completion of the survey by an occupant. Theoretically, completion of the survey should have triggered high levels of salience among respondents. If a lack of salience was the main obstacle to manual adjustments, completion of the survey should have increased manual adjustments.

182 responses coming from 156 unique rooms completed the survey by 11:59pm, November 24th (last day of temperature data collection, the remaining survey responses were received after Nov. 24th and therefore could not be included in this sub-analysis). Of these 156 rooms, only 43 (27.6 percent) experienced a manual adjustment after completion in the observed time frame. Among these 43 rooms, the average time passed between survey completion and the next manual adjustment was about 43.5 hours. Both of these statistics suggest that the salience explanation is not particularly explanatory in this context.

3.3.3.4 Ignorance

The ignorance explanation is that the default effect exists because people do not know that they can change the temperature. This explanation appears to have limited explanatory power in dorm rooms, as 76 percent of respondents said they knew they could adjust their dorm room thermostat (Table 3.13). This 24 percent of rooms that did not know how to adjust the temperature closely mirrors the percent of rooms in the Control who stayed at the default user adjustment value (Table 3.29). However, ignorance seems to play a larger role in communal spaces (Table 3.14), as only 28 percent of respondents indicated they knew how to adjust communal rooms' temperature (an odd finding, seeing as the mechanism is the same as in the dorm rooms).

Additionally, a more nuanced ignorance explanation emerged: a false perception that the thermostat was broken, perhaps fueled by a lack of knowledge about how the system worked, may have resulted in residents no longer adjusting temperatures because they thought it would make no difference. 28 percent of respondents believed their thermostat did not work, with an additional 45 percent responding that they were unsure if their thermostat worked (Table 3.15). Anecdotally, a handful of respondents wrote that they do not use their thermostat because they think it is broken. For

Table 3.13: Before this survey, did you know how to adjust the temperature of your dorm room?

Treatment	Yes	No
LF-G	26 (78.8%)	7 (21.2%)
HF-G	36 (80%)	9 (20%)
LF-A	32 (65.3%)	17 (34.7%)
HF-A	31 (77.5%)	9 (22.5%)
Control	49 (79%)	13 (21%)
Aggregate	178 (75.7%)	57 (24.3%)

Table 3.14: Before this survey, did you know how to adjust the temperature of communal rooms in your residence hall?

Treatment	Yes	No
LF-G	8 (24.2%)	25 (75.8%)
HF-G	11 (24.4%)	34 (75.6%)
LF-A	15 (30.6%)	34 (69.4%)
HF-A	8 (20%)	32 (80%)
Control	22 (35.5%)	40 (64.5%)
Aggregate	65 (27.7%)	170 (72.3%)

example, one respondent of the pilot survey wrote, "I've tried to [use the thermostat] once and it didn't work, so I never did so again." This perception was not grounded in reality: audits of all dorm rooms immediately following the pilot and Fall session (in both cases, approximately a month after the survey was distributed) found no evidence of broken thermostats. Nevertheless, this explanation clearly played a role in the findings.

Table 3.15: Do you believe your thermostat is functioning correctly?

Treatment	Yes	No	Unsure: I have used it but am not sure if it functions correctly	Unsure: I have never used it
LF-G	7 (21.2%)	7 (21.2%)	17 (51.5%)	2 (6.1%)
HF-G	8 (17.8%)	18 (40%)	16 (35.6%)	3 (6.7%)
LF-A	13 (26.5%)	14 (28.6%)	16 (32.7%)	6 (12.2%)
HF-A	12 (30%)	11 (27.5%)	13 (32.5%)	4 (10%)
Control	21 (33.9%)	13 (21%)	24 (38.7%)	4 (6.5%)
Aggregate	64 (27.2%)	64 (27.2%)	88 (37.4%)	19 (8.1%)

3.3.3.5 Social Considerations

There was evidence that this default effect was also fueled in part by social considerations (Tables and 3.16 3.17). 66 percent (for dorm rooms) and 59 percent (for communal rooms) of respondents indicated that other peoples' comfort played a role in their temperature decision-making process (the largest percentage out of all non-personal comfort factors listed in the question). As was said by one respondent regarding thermostats in communal spaces, "It's not my space alone so I should not have control over it."

Table 3.16: Other than comfort, do any of the following factors influence your decision on whether or not to adjust your dorm rooms' temperature?

Treatment	Other's comfort	Effort required	Length of time you plan to be in the room	Environmental impacts	No other factors
LF-G	23 (35.4%)	13 (20%)	14 (21.5%)	12 (18.5%)	1 (1.5%)
HF-G	31 (41.3%)	18 (24%)	12 (16%)	7 (9.3%)	6 (8%)
LF-A	30 (36.6%)	16 (19.5%)	16 (19.5%)	8 (9.8%)	9 (11%)
HF-A	25 (35.2%)	16 (22.5%)	15 (21.1%)	6 (8.5%)	7 (9.9%)
Control	43 (41%)	21 (20%)	19 (18.1%)	13 (12.4%)	8 (7.6%)
Aggregate	156 (38%)	86 (21%)	79 (19.3%)	48 (11.7%)	32 (7.8%)

Table 3.17: Other than comfort, do any of the following factors influence your decision on whether or not to adjust the communal rooms' temperature?

Treatment	Others' comfort	Effort required	Length of time you plan to be in the room	Environmental impacts	No other factors
LF-G	20 (35.7%)	8 (14.3%)	14 (25%)	6 (10.7%)	8 (14.3%)
HF-G	27 (36.5%)	15 (20.3%)	17 (23%)	6 (8.1%)	9 (12.2%)
LF-A	34 (37.8%)	15 (16.7%)	25 (27.8%)	6 (6.7%)	9 (10%)
HF-A	22 (33.3%)	12 (18.2%)	12 (18.2%)	5 (7.6%)	15 (22.7%)
Control	35 (35%)	18 (18%)	20 (20%)	9 (9%)	18 (18%)
Aggregate	140 (35.3%)	70 (17.6%)	92 (23.2%)	33 (8.3%)	61 (15.4%)

3.3.3.6 Green Guilt

Unique to green defaults, the guilt explanation suggests that the default effect exists because people feel guilt when considering switching away from the eco-friendly default, constraining them from doing so. The survey provided a limited amount of support for this explanation (Tables 3.16 and 3.17), with 20 percent (for dorm rooms) and 14 percent (for communal rooms) of respondents reporting that the environmental impacts of heating/cooling play a role in their temperature decision-making.

This lack of guilt may be connected to the respondents' worldview of environmental challenges such as climate change. Respondents seemed to believe that this intervention had implications for energy savings, as 81 percent agreed that the study was important for understanding how to conserve energy (Table 3.18). However, only 48 percent believed it helped the environment (Table 3.19). Underpowered evidence from a question only presented to respondents that responded affirmatively to the energy question and negatively to the environmental one (n = 8) suggests that students doubt that enough dorm rooms stayed at the energy-saving default to meaningfully benefit the environment, and also may consider the size of any possible energy conservation to be inconsequential when compared to the scale of climate change. For instance, one respondent wrote: "Larger cooperations [sic] have a much bigger impact on the environment than we ever will. Changing a few degrees in the dorms won't do as much as protesting bigger issues and making changes there". This would be an interesting area for further research, as disillusionment with individual sustainable decisions due to the global scale of the problem could prove a significant obstacle to collective change.

Table 3.18: Please indicate how much you agree the following statement: This study is important for understanding how to conserve energy

Treatment	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
LF-G	14 (42.4%)	17 (51.5%)	0 (0.0%)	1 (3.0%)	1 (3.0%)
HF-G	16 (35.6%)	20 (44.4%)	8 (17.8%)	1 (2.2%)	0 (0.0%)
LF-A	13 (26.5%)	25 (51.0%)	5 (10.2%)	4 (8.2%)	2 (4.1%)
HF-A	10 (25.0%)	20 (50.0%)	7 (17.5%)	2 (5.0%)	1 (2.5%)
Control	17 (27.4%)	35 (56.5%)	6 (9.7%)	3 (4.8%)	1 (1.6%)
Aggregate	71 (30.2%)	121 (51.5%)	27 (11.5%)	11 (4.7%)	5 (2.1%)

Table 3.19: Please indicate how much you agree with the following statement: This study had a positive impact on the environment

Treatment	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
LF-G	2 (6.1%)	17 (51.5%)	10 (30.3%)	2 (6.1%)	2 (6.1%)
HF-G	9 (20.0%)	13 (28.9%)	23 (51.1%)	0 (0.0%)	0 (0.0%)
LF-A	4 (8.2%)	20 (40.8%)	23 (46.9%)	2 (4.1%)	0 (0.0%)
HF-A	5 (12.5%)	11 (27.5%)	21 (52.5%)	2 (5.0%)	1 (2.5%)
Control	7 (11.3%)	23 (37.1%)	28 (45.2%)	2 (3.2%)	2 (3.2%)
Aggregate	28 (11.9%)	86 (36.6%)	108 (46.0%)	8 (3.4%)	5 (2.1%)

3.3.4 Emotional Reactance

To gauge the general impact of the session, respondents were informed that not all rooms were a part of the session due to the presence of the control group. Respondents were then asked to share if they thought their room was a part of a treatment or control group (Table 3.20). 109 respondents indicated they thought their room was in a treatment (46.4 percent), with 58 (24.7 percent) thinking their room was not and 68 (28.9 percent) being unsure. Among the 167 respondents that were in a treatment, only 84 (50 percent) thought they were a part of a treatment, with 26 (20.6 percent) thinking they were not and 37 (29.4 percent) being unsure. This uncertain sentiment appeared again in the next question, with only 60 respondents (25.5 percent) reported feeling negatively impacted by the study (Table 3.21). Further, respondents were asked if they felt the potential benefits (possible energy conservation) of this study outweigh the potential costs (possible uncomfortable temperatures). 126 respondents (53.6 percent) believe that the benefits are greater, 66 respondents (28.1 percent) think the costs and benefits are about the same, and 43 respondents (18.3 percent) think the costs are greater (Table 3.28). Responses to these questions indicate that the impact on the study was minimal, or at least not very noticeable and memorable.

Table 3.20: Based on your experiences this past month, do you believe that your dorm room was included in this study?

Treatment	Yes	No	I don't know
LF-G	17 (51.5%)	7 (21.2%)	9 (27.3%)
HF-G	24 (53.3%)	6 (13.3%)	15 (33.3%)
LF-A	25 (51.0%)	8 (16.3%)	16 (32.7%)
HF-A	18 (45.0%)	14 (35.0%)	8 (20.0%)
Control	22 (35.5%)	23 (37.1%)	17 (27.4%)
Aggregate	109 (46.4%)	58 (24.7%)	68 (28.9%)

Table 3.21: How do you believe this study personally impacted you?

Treatment	Strongly positive	Somewhat positive	Neutral	Somewhat negative	Strongly negative	I wasn't impacted
LF-G	1 (3%)	3 (9.1%)	17 (51.5%)	7 (21.2%)	0 (0%)	5 (15.2%)
HF-G	0 (0%)	1 (2.2%)	26 (57.8%)	11 (24.4%)	2 (4.4%)	5 (11.1%)
LF-A	0 (0%)	1 (2%)	19 (38.8%)	14 (28.6%)	5 (10.2%)	10 (20.4%)
HF-A	1 (2.5%)	1 (2.5%)	19 (47.5%)	8 (20%)	2 (5%)	9 (22.5%)
Control	0 (0%)	5 (8.1%)	31 (50%)	9 (14.5%)	1 (1.6%)	16 (25.8%)
Aggregate	2 (0.9%)	11 (4.7%)	115 (48.9%)	50 (21.3%)	10 (4.3%)	47 (20%)

To further understand the emotional impacts of the study, respondents were asked a series of questions which were modified from Heatherly, Baker and Canfield (2023)'s study on emotional reactance of smart thermostat schedules. It is worth emphasizing that emotional reactance was not the focus of this study. As such, the survey did not devote space to personality type questions that could provide more nuanced analysis on reactance. Another distinction between the Heatherly, Baker and Canfield (2023) study and this one is the participants of this study were informed of the remote adjustments significantly after the defaults were implemented (though they are still sharing their immediate reactions to learning). It has been noted that reactance is often highest at the beginning of a control struggle (Heatherly, Baker and Canfield, 2023).

In general, this study's respondents came across as having low levels of reactance, feeling mostly neutral or vaguely positive about the study. Three questions were adapted from Heatherly, Baker and Canfield (2023). First, residents were asked how they would describe their thoughts towards the study, with 46.8 percent reporting neutral thoughts, 34 percent having positive thoughts, and 19.2 percent thinking negative thoughts (Table 3.22). Second, respondents were asked if they felt the study tried to make decisions for them. 36.2 percent agreed, 31.5 percent were neutral, and 22.3 percent disagreed (Table 3.23). Finally, respondents were asked if the study tried to manipulate them. 14.5 percent agreed, 28.9 percent were neutral, and 56.6 percent disagreed (Table 3.24).

Table 3.22: Overall, how would you describe your thoughts toward this study?

Treatment	Extremely positive	Somewhat positive	Neither positive nor negative	Somewhat negative	Extremely negative
LF-G	1 (3%)	13 (39.4%)	16 (48.5%)	2 (6.1%)	1 (3%)
HF-G	1 (2.2%)	8 (17.8%)	24 (53.3%)	10 (22.2%)	2 (4.4%)
LF-A	1 (2%)	12 (24.5%)	22 (44.9%)	10 (20.4%)	4 (8.2%)
HF-A	3 (7.5%)	12 (30%)	19 (47.5%)	5 (12.5%)	1 (2.5%)
Control	2 (3.2%)	24 (38.7%)	26 (41.9%)	7 (11.3%)	3 (4.8%)
Aggregate	8 (3.4%)	72 (30.6%)	110 (46.8%)	34 (14.5%)	11 (4.7%)

Heatherly, Baker and Canfield (2023) examines the effect of language, justification type, and size of adjustment on emotional reactance. The protocol of this study maps closely to the "Has" language treatment and the transparent justification treatment. Thus, responses from this survey will be compared to the average of all responses in the Has-Transparent treatments.

Table 3.23: Please indicate how much you agree with the following statement: This study tried to make decisions for me

Treatment	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
LF-G	3 (9.1%)	8 (24.2%)	12 (36.4%)	6 (18.2%)	4 (12.1%)
HF-G	2 (4.4%)	13 (28.9%)	20 (44.4%)	6 (13.3%)	4 (8.9%)
LF-A	9 (18.4%)	11 (22.4%)	16 (32.7%)	7 (14.3%)	6 (12.2%)
HF-A	5 (12.5%)	9 (22.5%)	10 (25.0%)	8 (20.0%)	8 (20.0%)
Control	7 (11.3%)	17 (27.4%)	14 (22.6%)	17 (27.4%)	7 (11.3%)
Aggregate	26 (11.1%)	59 (25.1%)	74 (31.5%)	45 (19.1%)	31 (13.2%)

Table 3.24: Please indicate how much you agree with the following statement: This study tried to manipulate me

Treatment	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
LF-G	1 (3%)	3 (9.1%)	8 (24.2%)	10 (30.3%)	11 (33.3%)
HF-G	3 (6.7%)	5 (11.1%)	15 (33.3%)	6 (13.3%)	16 (35.6%)
LF-A	5 (10.2%)	5 (10.2%)	15 (30.6%)	14 (28.6%)	10 (20.4%)
HF-A	1 (2.5%)	2 (5%)	14 (35%)	7 (17.5%)	16 (40%)
Control	4 (6.5%)	5 (8.1%)	14 (22.6%)	15 (24.2%)	24 (38.7%)
Aggregate	14 (6%)	20 (8.5%)	68 (28.9%)	54 (23%)	79 (33.6%)

The average score for residents describing their thoughts towards the study was 2.86 (between somewhat positive and neutral), compared to Heatherly, Baker and Canfield (2023)'s 2.26 score (between somewhat positive and neutral). The average score when respondents were asked if they felt the study tried to make decisions for them was 2.98 (between somewhat agree and neutral), and the average score when respondents were asked if the study tried to manipulate them was 3.7 (between neutral and somewhat disagree). These scores average to 3.34 (between neutral and somewhat disagree), compared to Heatherly, Baker and Canfield (2023)'s Threat to Freedom score of 2.47 (between somewhat agree and neutral). Thus, respondents in this study had a slightly less favorable outlook of the study than Heatherly, Baker and Canfield (2023), but experienced less emotional reactance than respondents in Heatherly, Baker and Canfield (2023). The drop in favor-ability could be a product of this session being real, as opposed to a hypothetical survey. The decreased Threat to Freedom could be due to multiple factors, including this study making smaller temperature adjustments than Heatherly, Baker and Canfield (2023) did, and respondent uncertainty surrounding whether or not they were in the control and impacted at all.

Additionally, respondents' approximate WTA for another semester of enrollment in the default remote temperature adjustment schedules were approximated in the survey (Tables 3.25, 3.26, 3.27). Two respondent types of interest emerged: respondents with a low WTA of 5 dollars or lower (76 responses, 32 percent) and respondents with a high WTA of 25 dollars or greater (72 responses, 31 percent). The average scores of the three reactance questions discussed above were calculated for each of these subgroups.

Table 3.25: Would you accept $10 to have your dorm room enrolled in this study next semester?

Treatment	Yes, I would accept the $10	No, I would not accept the $10
LF-G	21 (63.6%)	12 (36.4%)
HF-G	23 (51.1%)	22 (48.9%)
LF-A	30 (61.2%)	19 (38.8%)
HF-A	26 (65%)	14 (35%)
Control	40 (64.5%)	22 (35.5%)
Aggregate	141 (60%)	94 (40%)

Table 3.26: Would you accept $5 to have your dorm room enrolled in this study next semester?

Treatment	Yes, I would accept the $5	No, I would not accept the $5
LF-G	13 (39.4%)	8 (24.2%)
HF-G	10 (22.2%)	13 (28.9%)
LF-A	17 (34.7%)	13 (26.5%)
HF-A	15 (37.5%)	11 (27.5%)
Control	21 (33.9%)	19 (30.6%)
Aggregate	76 (32.3%)	65 (27.7%)

Those with High WTA averaged 3.14 (between neutral and somewhat negative) for the question regarding general thoughts, 2.93 (between somewhat agree and

Table 3.27: Would you accept $25 to have your dorm room enrolled in this study next semester?

Treatment	Yes, I would accept the $25	No, I would not accept the $25
LF-G	1 (3%)	11 (33.3%)
HF-G	6 (13.3%)	16 (35.6%)
LF-A	3 (6.1%)	16 (32.7%)
HF-A	4 (10%)	10 (25%)
Control	6 (9.7%)	16 (25.8%)
Aggregate	22 (9.4%)	72 (30.6%)

neutral) for the question asking if the study was making decisions for them, and 3.58 (between neutral and somewhat disagree) for the question about possible manipulation (3.26 Threat to Freedom average). Conversely, the Low WTA respondents averaged 2.63 (between somewhat positive and neutral), 3.45 (between neutral and somewhat disagree), and 4.03 (between somewhat disagree and strongly disagree; 3.74 Threat to Freedom average) for all questions, respectively. For all three questions, the Low WTA group demonstrates a more positive outlook by about half a point. However, while about a third of the survey respondents displayed a High WTA and more emotional reactance, even this subgroup experienced more than a full point less Threat to Freedom compared to Heatherly, Baker and Canfield (2023)'s participants, and had mostly neutral thoughts on the session.

Table 3.28: Do you feel the potential benefits (possible energy conservation) of this study outweigh the potential costs (possible uncomfortable temperatures)?

Treatment	Benefits are significantly greater	Benefits are somewhat greater	Benefits and costs are about the same	Costs are somewhat greater	Costs are significantly greater
LF-G	9 (27.3%)	10 (30.3%)	8 (24.2%)	5 (15.2%)	1 (3%)
HF-G	6 (13.3%)	13 (28.9%)	15 (33.3%)	8 (17.8%)	3 (6.7%)
LF-A	5 (10.2%)	24 (49%)	10 (20.4%)	5 (10.2%)	5 (10.2%)
HF-A	4 (10%)	17 (42.5%)	13 (32.5%)	5 (12.5%)	1 (2.5%)
Control	10 (16.1%)	25 (40.3%)	18 (29%)	5 (8.1%)	4 (6.5%)
Aggregate	35 (14.9%)	91 (38.7%)	66 (28.1%)	29 (12.3%)	14 (6%)

Table 3.29: Default Effect and Average Treatment Effect

Treatment		Week 0	Week 1	Week 2	Week 3	Week 4	Full Session	Week 5	Week 6
Control									
	Default User Adjustment	0	0	0	0	0	0	0	0
	Percent obs. at default 100% of time	55.26%	31.58%	27.19%	27.19%	24.56%	23.68%	24.56%	22.81%
	Percent obs. at default 90%+ of time	56.14%	32.46%	28.07%	27.19%	25.44%	23.68%	25.44%	22.81%
	Percent obs. at default 50%+ of time	62.28%	37.72%	30.7%	28.07%	27.19%	25.44%	27.19%	27.19%
Low Frequency - Gradual									
	Default User Adjustment	0	0	-1	-2	-3	variable	-3	-3
	Percent obs. at default 100% of time	54.63%	46.30%	51.85%	57.41%	86.11%	32.41%	86.11%	78.7%
	Percent obs. at default 90%+ of time	55.56%	50%	55.56%	60.19%	87.04%	36.11%	87.96%	78.7%
	Percent obs. at default 50%+ of time	58.33%	55.56%	62.96%	85.19%	96.30%	45.37%	91.67%	86.11%
	Average Treatment Effect		0.604***	0.190***	-0.210***	-0.975***		-0.901***	-0.841***
			(0.016)	(0.016)	(0.016)	(0.016)		(0.016)	(0.016)
High Frequency - Gradual									
	Default User Adjustment	0	0	-1	-2	-3	variable	-3	-3
	Percent obs. at default 100% of time	65.18%	52.68%	42.86%	66.07%	83.93%	28.57%	83.04%	81.25%
	Percent obs. at default 90%+ of time	67.86%	58.04%	46.43%	75.89%	87.50%	32.14%	84.82%	83.04%
	Percent obs. at default 50%+ of time	75.00%	83.04%	83.04%	91.07%	98.21%	75.00%	87.50%	84.82%
	Average Treatment Effect		0.753***	0.187***	-0.567***	-1.467***		-1.112***	-1.111***
			(0.017)	(0.017)	(0.017)	(0.017)		(0.017)	(0.018)
Low Frequency - Abrupt									
	Default User Adjustment	0	-3	-3	-3	-3	-3	-3	-3
	Percent obs. at default 100% of time	51.33%	84.07%	76.99%	72.57%	84.96%	63.72%	84.07%	76.11%
	Percent obs. at default 90%+ of time	52.21%	86.73%	77.88%	75.22%	88.50%	66.37%	85.84%	77.88%
	Percent obs. at default 50%+ of time	59.29%	92.04%	87.61%	97.35%	96.46%	82.30%	91.15%	88.50%
	Average Treatment Effect		-1.229***	-0.912***	-0.888***	-1.034***		-0.895***	-0.871***
			(0.015)	(0.015)	(0.015)	(0.015)		(0.015)	(0.016)
High Frequency - Abrupt									
	Default User Adjustment	0	-3	-3	-3	-3	-3	-3	-3
	Percent obs. at default 100% of time	46.79%	79.82%	79.82%	73.39%	77.98%	64.22%	83.49%	77.06%
	Percent obs. at default 90%+ of time	49.54%	88.07%	84.40%	78.90%	84.40%	72.48%	85.32%	78.90%
	Percent obs. at default 50%+ of time	59.63%	97.25%	96.33%	97.25%	95.41%	94.50%	88.99%	83.49%
	Average Treatment Effect		-1.282***	-1.154***	-1.006***	-0.992***		-0.838***	-0.807***
			(0.016)	(0.016)	(0.016)	(0.016)		(0.016)	(0.016)

Table 3.30: User Adjustment Regression Results

	Dependent variable: User Adjustment					
	Fixed Effects		**Random Effects**		**Tobit Models**	
	No Interactions	Interactions	No Interactions	Interactions	No Interactions	Interactions
Treatment LF-G			−0.497*** (0.108)	−0.178 (0.109)	−0.992*** (0.012)	−0.287*** (0.045)
Treatment HF-G			−0.234** (0.118)	0.269** (0.119)	−0.444*** (0.013)	0.355*** (0.048)
Treatment LF-A			−1.092*** (0.107)	−0.167 (0.108)	−3.229*** (0.015)	−0.226*** (0.044)
Treatment HF-A			−1.109*** (0.110)	−0.141 (0.111)	−3.428*** (0.016)	−0.222*** (0.045)
Week 1	−0.853*** (0.006)	−0.571*** (0.011)	−0.853*** (0.006)	−0.571*** (0.011)	−1.766*** (0.019)	−0.869*** (0.036)
Week 2	−1.088*** (0.006)	−0.727*** (0.011)	−1.088*** (0.006)	−0.727*** (0.011)	−2.019*** (0.019)	−1.096*** (0.036)
Week 3	−1.353*** (0.006)	−0.826*** (0.006)	−1.353*** (0.011)	−0.826*** (0.011)	−2.325*** (0.019)	−1.227*** (0.036)
Week 4	−1.701*** (0.006)	−0.845*** (0.011)	−1.701*** (0.006)	−0.845*** (0.011)	−4.170*** (0.021)	−1.293*** (0.036)
Week 5	−1.625*** (0.006)	−0.901*** (0.011)	−1.625*** (0.006)	−0.901*** (0.011)	−3.824*** (0.021)	−1.417*** (0.036)
Week 6	−1.527*** (0.006)	−0.827*** (0.006)	−1.527*** (0.011)	−0.827*** (0.011)	−3.419*** (0.021)	−1.316*** (0.038)
Treatment LF-G, Week 1		0.604*** (0.016)		0.604*** (0.016)		0.915*** (0.052)
Treatment HF-G, Week 1		0.753*** (0.017)		0.753*** (0.017)		1.163*** (0.055)
Treatment LF-A, Week 1		−1.229*** (0.015)		−1.229*** (0.015)		−3.591*** (0.056)
Treatment HF-A, Week 1		−1.282*** (0.016)		−1.282*** (0.016)		−3.850*** (0.059)
Treatment LF-G, Week 2		0.190*** (0.016)		0.190*** (0.016)		0.606*** (0.052)
Treatment HF-G, Week 2		0.187*** (0.017)		0.187*** (0.017)		0.692*** (0.055)
Treatment LF-A, Week 2		−0.912*** (0.015)		−0.912*** (0.015)		−2.495*** (0.054)
Treatment HF-A, Week 2		−1.154*** (0.016)		−1.154*** (0.016)		−3.981*** (0.061)
Treatment LF-G, Week 3		−0.210*** (0.016)		−0.210*** (0.016)		0.403*** (0.052)
Treatment HF-G, Week 3		−0.567*** (0.017)		−0.567*** (0.017)		0.013 (0.055)
Treatment LF-A, Week 3		−0.888*** (0.015)		−0.888*** (0.015)		−2.764*** (0.055)
Treatment HF-A, Week 3		−1.006*** (0.016)		−1.006*** (0.016)		−3.469*** (0.059)
Treatment LF-G, Week 4		−0.975*** (0.016)		−0.975*** (0.016)		−3.453*** (0.058)
Treatment HF-G, Week 4		−1.467*** (0.017)		−1.467*** (0.017)		−4.534*** (0.067)
Treatment LF-A, Week 4		−1.034*** (0.015)		−1.034*** (0.015)		−3.876*** (0.059)
Treatment HF-A, Week 4		−0.992*** (0.016)		−0.992*** (0.016)		−3.377*** (0.059)
Treatment LF-G, Week 5		−0.901*** (0.016)		−0.901*** (0.016)		−3.102*** (0.057)
Treatment HF-G, Week 5		−1.112*** (0.017)		−1.112*** (0.017)		−2.812*** (0.060)
Treatment LF-A, Week 5		−0.895*** (0.015)		−0.895*** (0.015)		−2.995*** (0.056)
Treatment HF-A, Week 5		−0.838*** (0.016)		−0.838*** (0.016)		−2.720*** (0.057)
Treatment LF-G, Week 6		−0.841*** (0.016)		−0.841*** (0.016)		−2.377*** (0.058)
Treatment HF-G, Week 6		−1.111*** (0.018)		−1.111*** (0.018)		−2.652*** (0.062)
Treatment LF-A, Week 6		−0.871*** (0.016)		−0.871*** (0.016)		−2.537*** (0.057)
Treatment HF-A, Week 6		−0.807*** (0.016)		−0.807*** (0.016)		−2.302*** (0.058)
Constant			−0.325*** (0.076)	−0.864*** (0.076)	0.314*** (0.018)	−1.190*** (0.031)
Observations	489,472	489,472	489,472	489,472	489,472	489,472
R^2	0.218	0.388	0.218	0.388		
Adjusted R^2	0.217	0.387	0.218	0.388		
Log Likelihood					−529,491.200	−500,919.300
Wald Test					112,237.600*** (df = 10)	146,633.700*** (df = 34)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.31: Space Temperature Regression Results

	Dependent variable:			
	Space Temperature			
	Fixed Effects		**Random Effects**	
	No Interactions	Interactions	No Interactions	Interactions
Treatment LF-G			0.016	0.122
			(0.107)	(0.107)
Treatment HF-G			0.201*	0.440***
			(0.116)	(0.117)
Treatment LF-A			−0.518***	0.076
			(0.105)	(0.106)
Treatment HF-A			−0.578***	0.030
			(0.108)	(0.109)
Week 1	−0.764***	−0.564***	−0.764***	−0.564***
	(0.005)	(0.010)	(0.005)	(0.010)
Week 2	−1.024***	−0.842***	−1.024***	−0.842***
	(0.005)	(0.010)	(0.005)	(0.010)
Week 3	−1.087***	−0.818***	−1.087***	−0.818***
	(0.005)	(0.010)	(0.005)	(0.010)
Week 4	−1.450***	−0.939***	−1.450***	−0.939***
	(0.005)	(0.010)	(0.005)	(0.010)
Week 5	−1.413***	−0.962***	−1.413***	−0.962***
	(0.005)	(0.010)	(0.005)	(0.010)
Week 6	−1.540***	−1.180***	−1.540***	−1.180***
	(0.005)	(0.010)	(0.005)	(0.010)
Treatment LF-G, Week 1		0.438***		0.438***
		(0.014)		(0.014)
Treatment HF-G, Week 1		0.547***		0.547***
		(0.016)		(0.016)
Treatment LF-A, Week 1		−0.872***		−0.872***
		(0.014)		(0.014)
Treatment HF-A, Week 1		−0.928***		−0.928***
		(0.015)		(0.015)
Treatment LF-G, Week 2		0.263***		0.263***
		(0.014)		(0.014)
Treatment HF-G, Week 2		0.264***		0.264***
		(0.016)		(0.016)
Treatment LF-A, Week 2		−0.600***		−0.600***
		(0.014)		(0.014)
Treatment HF-A, Week 2		−0.739***		−0.739***
		(0.015)		(0.015)
Treatment LF-G, Week 3		0.056***		0.056***
		(0.014)		(0.014)
Treatment HF-G, Week 3		−0.169***		−0.169***
		(0.016)		(0.016)
Treatment LF-A, Week 3		−0.567***		−0.567***
		(0.014)		(0.014)
Treatment HF-A, Week 3		−0.654***		−0.654***
		(0.015)		(0.015)
Treatment LF-G, Week 4		−0.569***		−0.569***
		(0.014)		(0.014)
Treatment HF-G, Week 4		−0.886***		−0.886***
		(0.016)		(0.016)
Treatment LF-A, Week 4		−0.626***		−0.626***
		(0.014)		(0.014)
Treatment HF-A, Week 4		−0.592***		−0.592***
		(0.015)		(0.015)
Treatment LF-G, Week 5		−0.551***		−0.551***
		(0.014)		(0.014)
Treatment HF-G, Week 5		−0.738***		−0.738***
		(0.016)		(0.016)
Treatment LF-A, Week 5		−0.554***		−0.554***
		(0.014)		(0.014)
Treatment HF-A, Week 5		−0.503***		−0.503***
		(0.015)		(0.015)
Treatment LF-G, Week 6		−0.367***		−0.367***
		(0.015)		(0.015)
Treatment HF-G, Week 6		−0.612***		−0.612***
		(0.016)		(0.016)
Treatment LF-A, Week 6		−0.514***		−0.514***
		(0.015)		(0.015)
Treatment HF-A, Week 6		−0.379***		−0.379***
		(0.015)		(0.015)
Constant			73.343***	73.032***
			(0.075)	(0.075)
Observations	489,472	489,472	489,472	489,472
R^2	0.220	0.329	0.220	0.329
Adjusted R^2	0.219	0.328	0.220	0.329
Note:				*p<0.1; **p<0.05; ***p<0.01

3.4 2025 Results

Using the methods described in Section 2.7, Table 3.32 shows the energy and cost data across the 3-week session, at the room level. In the Control, the average daily energy consumption per room was 4,635.09 BTUs and the average daily cost per room was \$0.021. In Treatment 1 (which had efficient setpoints but no default reinforcements), across the session the average daily energy consumption per room was 3,332.13 BTUs (28.1% reduction relative to Control) and the average daily cost per room was \$0.015 (28.6% reduction relative to Control). In Treatment 2 (which had both efficient setpoints and weekly default reinforcements), average daily energy consumption per room was 2,951.54 BTUs (36.3% reduction relative to Control) and the average daily cost per room was \$0.013 (38.1% reduction relative to Control).

Table 3.32: Room Level Average BTU and Cost

Treatment	Avg. VLV	Avg. BTU/day	Avg. Cost/day (\$)	Count
1	2.42	3,332.13	0.015	146
2	2.26	2,951.54	0.013	171
Control	3.58	4,635.09	0.021	248

If these numbers are scaled to all 566 rooms and a semester's worth of time (15 weeks), the energy and cost figures can be seen in Table 3.33. Over a semester an expected savings of 77.4 MMBTUs and \$356.58 would be incurred from lowering the heating setpoint. An additional 22.6 MMBTUs and \$118.86 (for a grand total of 100.1 MMBTUs and \$475.44) can be saved by resetting the user adjustment value to 0 once a week. These figures are rough estimates, however, as FCU energy use and energy costs are highly variable depending on the season and weather.

These numbers can be further understood by examining the amount of time FCUs in each treatment spent heating the space, cooling the space, and inactive (Table 3.34). Both Treatments 1 and 2 spent slightly less time active than the control (64% and 65%, compared to 63%). This increase in inactivity was not evenly distributed between heating and cooling time, however, with Treatments 1 and 2 both spending

Table 3.33: Expected Semester Long Energy and Cost Numbers

Treatment	MMBTUs	Cost ($)
1	198.03	$891.45
2	175.41	$772.59
Control	275.46	$1,248.03

less time cooling (11% and 13%, compared to 16%) but more time heating (24% and 22%, compared to 20%).

Table 3.34: Percent of Time FCUs Spent in Various Modes

Treatment	Heating Time	Cooling Time	Time Inactive
1	24%	11%	64%
2	22%	13%	65%
Control	20%	16%	63%

These figures help make sense of the decrease in cost observed among the treatments, as FCUs we both active less in general and spent significantly less time in cooling mode even when active (which is more expensive than heating mode). However, it is less intuitive why energy consumption decreased despite an increase in heating time (which is more energy intensive than cooling). A likely explanation for this is that, when the FCUs in the treatments were active, they were using less energy than the Control FCUs. As can be seen in Table 3.35, when FCUs in the control were active they had an average valve position of 8.2%. In contrast, Treatment 1's average valve position was 5.7% and Treatment 2's average valve position was 5.9%. My understanding in communications with Facilities is that this is true at least in part because it takes less energy to heat a room from 68 degrees to 69 degrees (the treatment heating setpoint) than it does to heat a room from 71 degrees to 72 degrees (the control heating setpoint).

Table 3.35: Average FCU Valve Position When Active

Treatment	Avg. VLV When Active
1	5.74%
2	5.86%
Control	8.21%

A possible confounding variable is that both Treatments had cooler space temperatures prior to the session, with Treatment 1 being 1.68 degrees cooler and Treatment 2 being 1.19 degrees cooler (Table 3.36). Seeing as less heat is required to warm a cooler space, this discrepancy plausibly had a significant impact on energy use. This space temperature discrepancy was less pronounced during the actual session, though, with Treatment 1 have an average session space temperature only 1.25 degrees cooler and Treatment 2 being only 0.86 degrees cooler. Treatment 2 created greater energy savings despite being warmer than Treatment 1 both in the baseline and the session, indicating that more factors influence FCU energy use than only the space temperature. Further, even if all rooms started at the same space temperature. it would be expected that temperatures in the treatments gradually decreased to cooler levels over time during winter. Therefore, these savings can also be thought of as a window into what savings would be after this decline took place.

Table 3.36: Average Space Temperatures - 2025 Session

Treatment	Week 0	Week 1	Week 2	Week 3	Session Average
1	69.63	70.87	70.65	71.26	70.91
2	70.12	71.15	70.99	71.77	71.30
Control	71.31	72.22	71.99	72.26	72.16

Chapter 4

CONCLUSION

This study adds to the growing literature surrounding defaults and temperature decisions, reinforcing the notion that default effects do exist in the temperature realm. We test the effect of energy-efficient temperature default adjustment schedules using a field experiment across 566 dorm rooms at the University of Delaware. This study takes a much more modest approach than many other studies in the literature, however, with the default only lying about 1°F cooler than the averaged preferred setting (other studies such as Brown et al. (2013) push occupants more in the neighborhood of 3 to 5°F). This limited level of impact allowed an opportunity to measure emotional reactance to a small intervention, with results indicating that only a small subset of occupants feel negative emotions to such a default. This combination of a default effect and very limited emotional reactance suggest that small energy-saving defaults are a promising avenue for building managers looking to cut energy costs at the margins without ruffling feathers.

The small scale of the intervention also allowed existing relationships in the literature to be tested at a micro-scale. Notably, this study did not support the idea that gradual temperature adjustment are more effective and palatable than abrupt adjustment. While this may be true with larger adjustments (*e.g.*, Somasundaram, Koch and Lim (2023)), this study suggests that building managers making only small adjustments (say, a degree or two) perhaps do not need to worry about gradually ascending/descending to the desired level.

This study also contributes to the literature by providing survey insights into the psychological channels through which the default effect operates in the temperature setting. Results show that effort required to adjust the temperature and a lack of knowledge about how to use a thermostat are the main levers through which the default effect takes hold. This suggests that initiatives that building managers may take to encourage occupants to use less HVAC energy (*e.g.*, formal temperature recommendations, eco-friendly pleas) may not be effective. Furthermore, educational campaigns aimed at thermostat use could potentially backfire, as they could remove the ignorance barrier that kept many occupants at the default. Further, this study displays how decision-makers' ignorance surrounding their ability to switch away from a default can make a meaningful impact. This possibility has been discussed before (*e.g.*, Blumenstock, Callen and Ghani (2018)), but is not prominently discussed. It may be wise for future default studies to explicitly check if decision-makers know they can switch away from the default, or even education decision-makers before the intervention.

This study also provides insight into how dorm temperature decision-making compares to other settings in the literature, particularly homes. While home occupants typically do not adjust the thermostat in energy-saving ways (Brandon et al., 2022), dorm occupants in this study tended to prefer cooler temperatures despite the cool temperatures outside. Another distinction between dorms and homes is that there is typically no financial incentive to conserve energy in residence halls. Particularly in the smart thermostat default literature, residents are motivated to participate in and abide by default programs because they save money by doing so. Eliminating this incentive provides a more isolated view of behavior.

The major limitation of this study was the gap between user adjustment and space temperature. This, coupled with the -3 degree cap on user adjustments, limited how distinct the temperatures of the treatments could be made from each other and the control. A setting with greater control and flexibility would enable cleaner distinctions and stable temperatures across treatment. Furthermore, much of the survey is vulnerable to reporting bias. For example, residents may have experienced a halo effect for questions related to green guilt, overstating their actual environmental considerations. Broadly, any survey requiring recollection of past events, experiences, etc. is likely experiencing some level of bias due to forgetfulness and false memories.

Further, results derived from linking survey responses and room data can also only be considered circumstantial because the room's temperature decisions could be made by a roommate of the survey respondent. The skew of female respondents is a potential limitation as well because previous studies indicate that males and female make different temperature decisions (Brown et al., 2013).

It should also be noted that the energy savings found in this study (and all other similar studies) are only generalizable to buildings/campuses of the same design in the same climate. Relatively small details such as the location of the fan in the FCU can have over-sized influences on energy consumption of the system, as do the methods that produce and distribute the heated/chilled water used by the HVAC system. While the behavioral findings of this paper (WEIRD people willingly abide by small temperature adjustments in dorms) ought to be generalizable, energy implications of this behavior will widely vary. It is also worth noting that UD pays below market-price rates for electricity and, to a lesser extent, gas. This discount means that the dollar savings observed in this study are lower than that which would be enjoyed by entities paying market prices.

It is also of note that this session took place in the winter. Results from the pilot seemed to imply that summer sessions create much more reactance (but also have a higher potential energy savings). Future studies could apply similar default interventions during warm months, making the default temperature warmer. Future studies could also aim to build treatment designs based around specific psychological channels (*e.g*, some treatments have an app on their phone to adjust temperature, others do not). Further, the students in this study were primarily WEIRD. This is of note, as it is well documented that individuals Western, educated, industrialized, rich and democratic (WEIRD) societies do not always behave in a way that is representative of all peoples (Henrich, Heine and Norenzayan, 2010).

Welfare implications from a default effect that is partially accredited to ignorance are also unclear. Welfare impacts of defaults specifically appear to be complex, highly model-specific, and not thoroughly studied (Bernheim, Fradkin and Popov

(2015); Chesterley (2017)). In general, however, if a decision-maker is clouded by biases (inattention, faulty assumptions, etc.) and thus makes choices that do not optimize their private utility, nudges can increase welfare. This can be achieved in two ways: 1.) by reducing the influence of the biases on the decision-making process and/or 2.) by resulting in a more privately optimal choice (Allcott et al., 2022). If neither of these conditions are met, nudges are likely not the most efficient policy option (List et al., 2023).

Assessing these two conditions in this setting, ignorance is essentially a faulty assumption (the thermostats do not work). The default intervention does nothing to counteract this bias, rather it actively leverages this bias. It is possible that the default still resulted in a more optimal temperature decision than would have otherwise been made. Indeed, the neutral to somewhat positive average perceptions of the study may indicate this. The actual preferred user adjustment value of each room is not (and perhaps cannot be) known, however, which inherently creates uncertainty surrounding the welfare effects of this intervention. Further research can alleviate this concern by ensuring all residents know how to work the thermostat.

Building energy consumption and, more broadly, individual resource consumption are likely to continue to be pressing issues in the sustainability realm for the foreseeable future. This study leveraged defaults in the temperature realm, illustrating that periodically resetting thermostat settings to a default can both influence occupant behavior and save energy. These findings add to the temperature default literature, particularly in the realms of small temperature adjustments and psychological channels driving default effects. While temperature defaults alone may not make a large impact on energy sustainability, they nevertheless appear an effective, low-risk tool to improve the margins.

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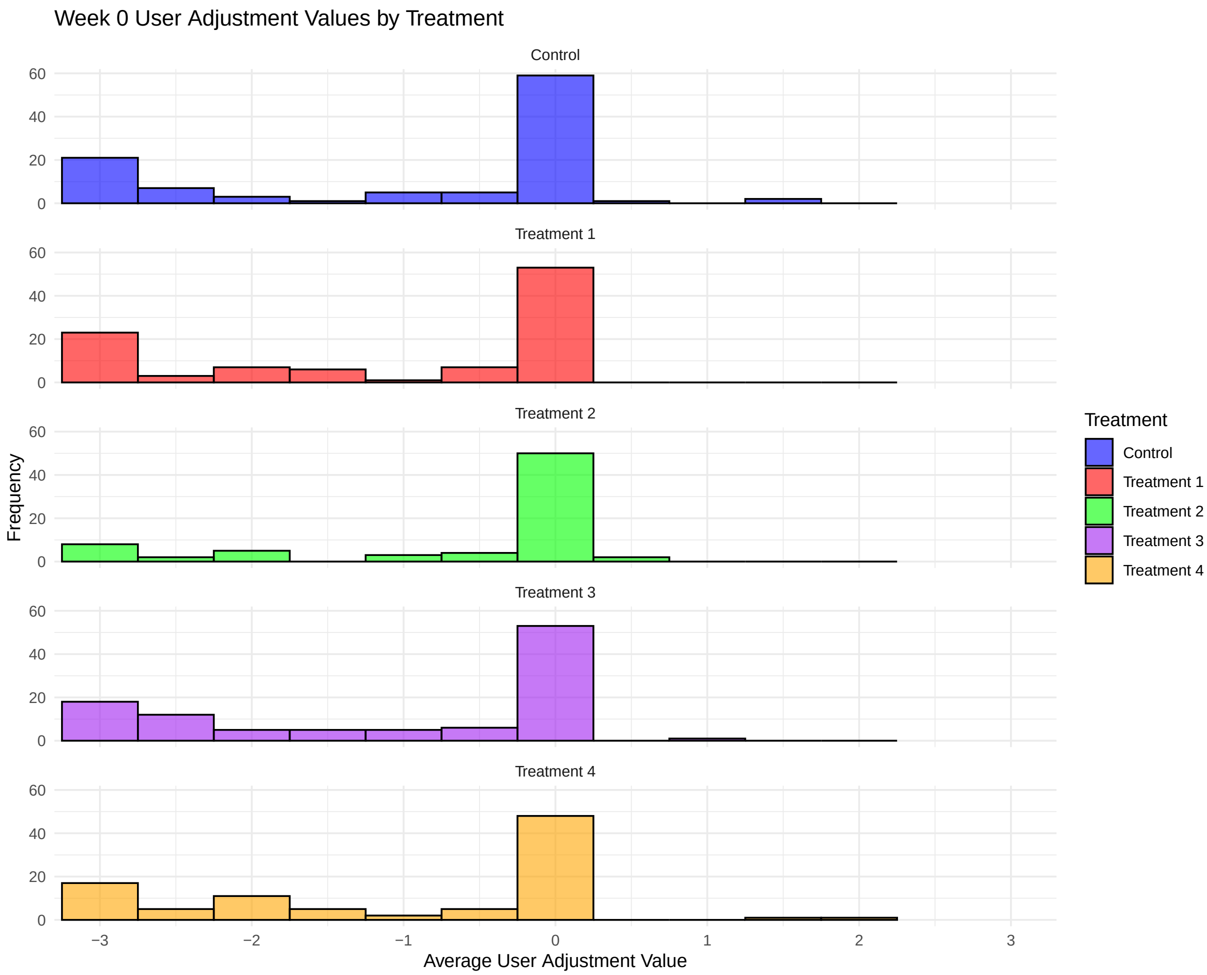
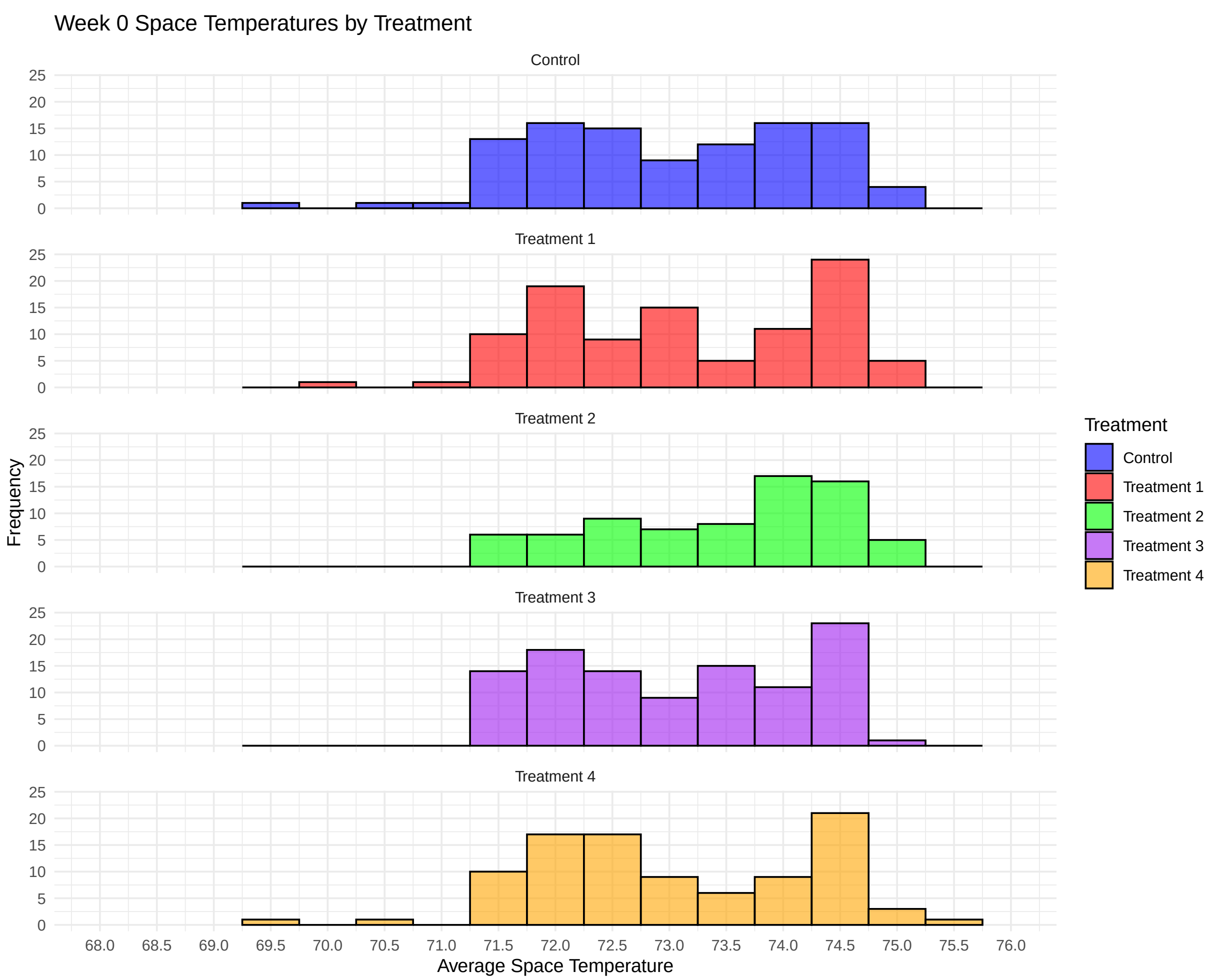
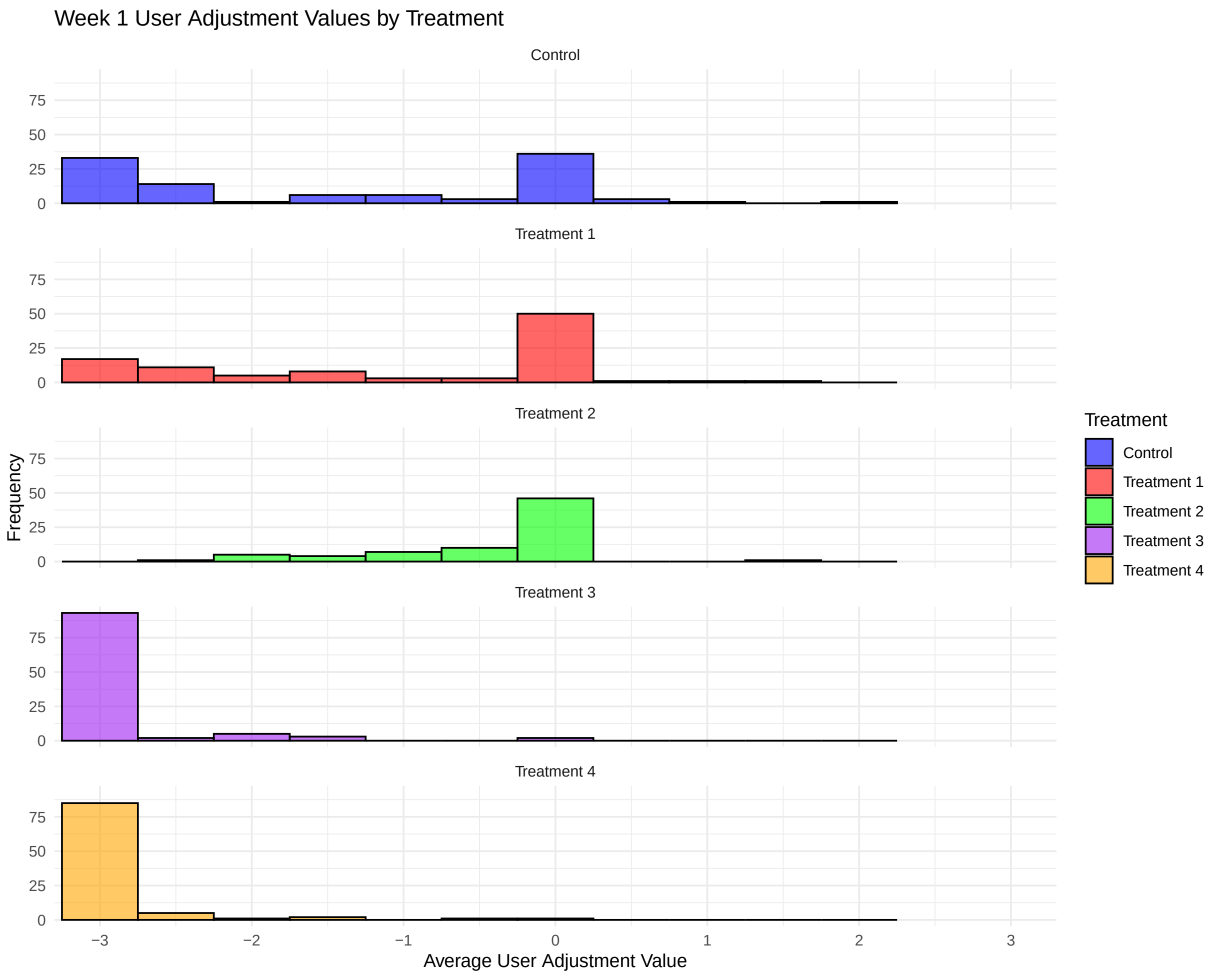
Appendix

APPENDIX A

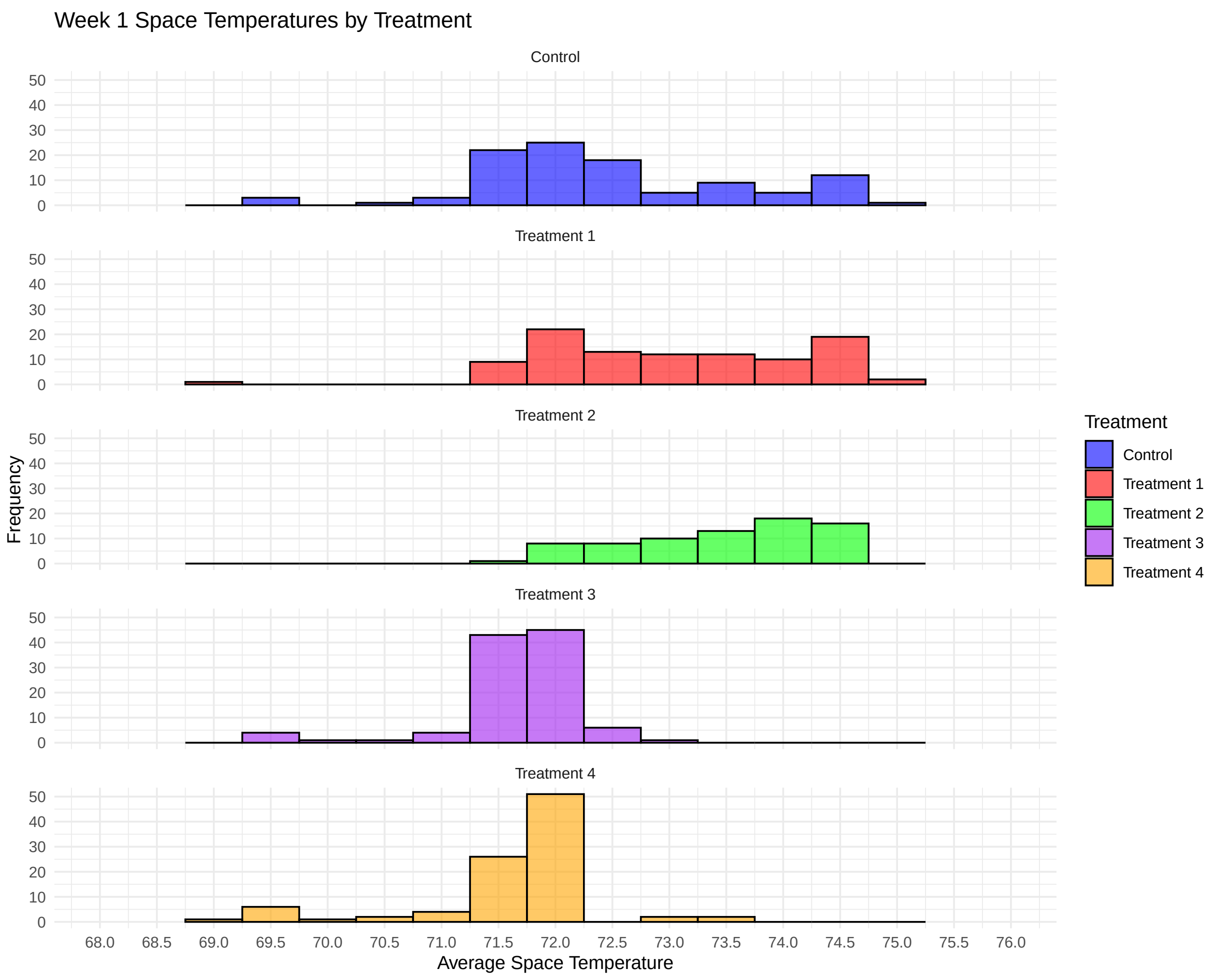
A.1 Histograms


Week 0 User Adjustment Values by Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
Frequency
Average User Adjustment Value
60
40
20
0
−3
−2
−1
0
1
2
3
Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4


Week 0 Space Temperatures by Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
Frequency
Average Space Temperature
Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4



Week 1 User Adjustment Values by Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
75
50
25
0
Frequency
−3
−2
−1
0
1
2
3
Average User Adjustment Value
Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4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Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
Frequency
Average Space Temperature
Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
0
10
20
30
40
50
68.0
68.5
69.0
69.5
70.0
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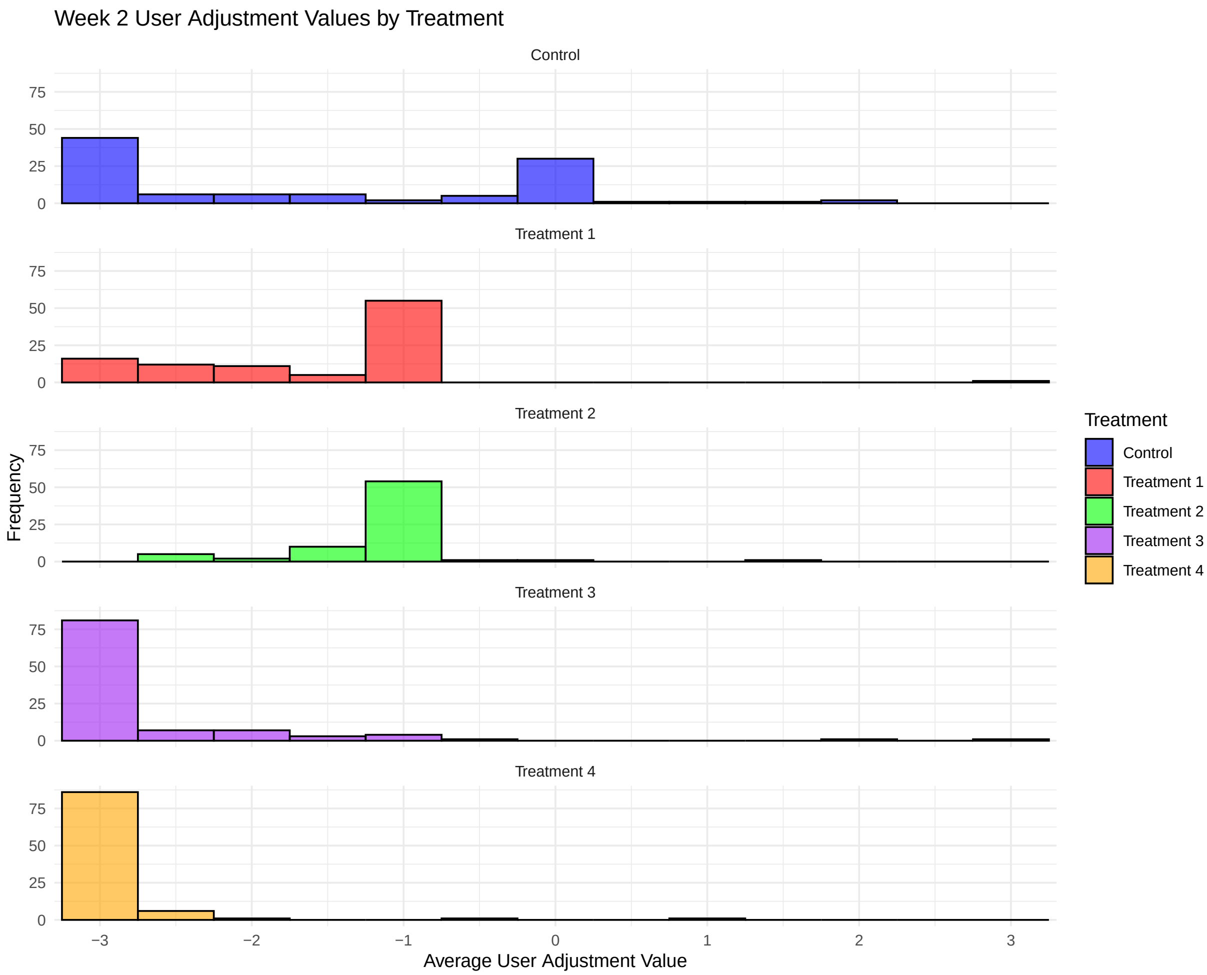
75.0
75.5
76.0


Week 2 User Adjustment Values by Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
Frequency
0
25
50
75
−3
−2
−1
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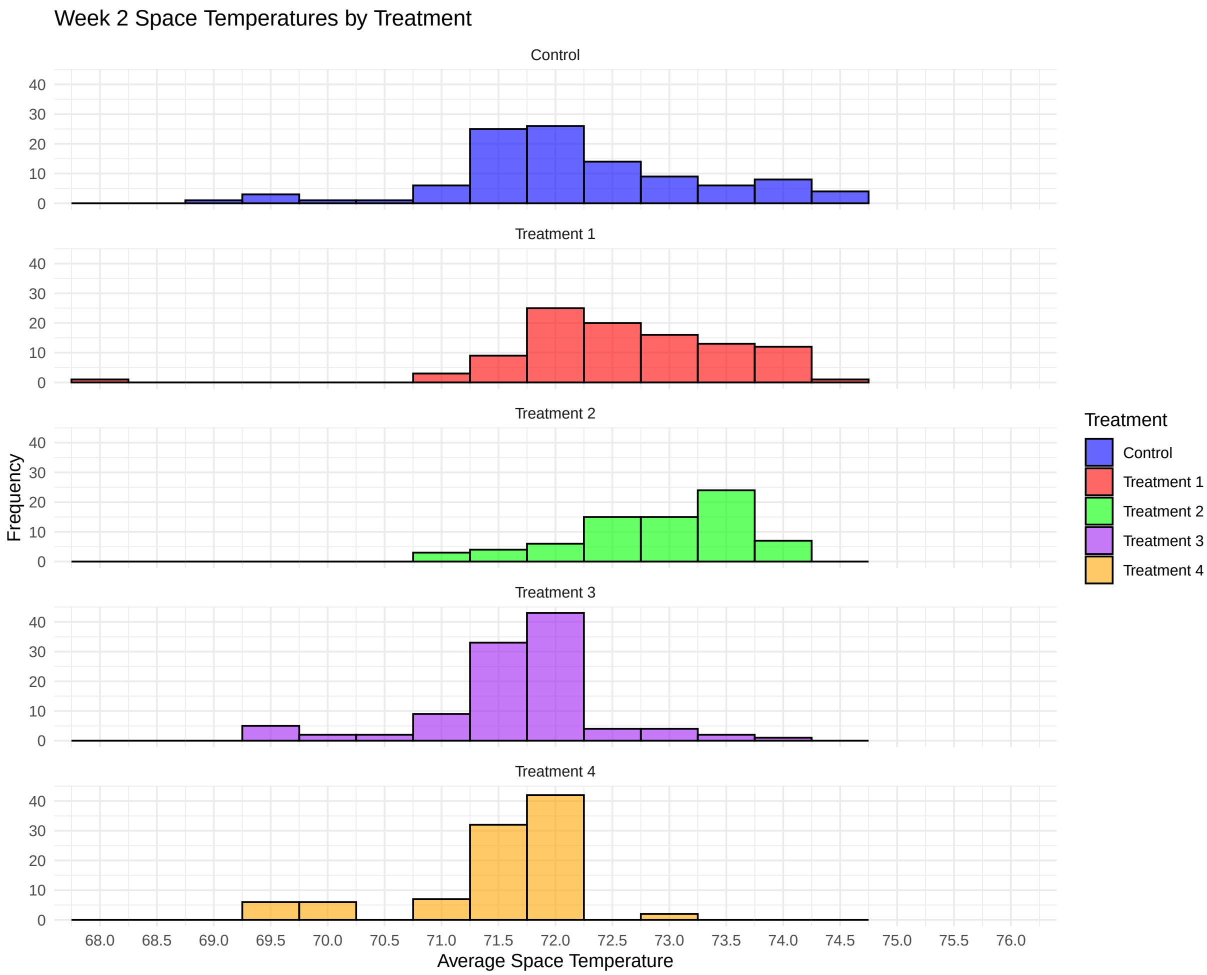
3
Average User Adjustment Value
Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4


Week 2 Space Temperatures by Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
Frequency
Average Space Temperature
Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
0
10
20
30
40
68.0
68.5
69.0
69.5
70.0
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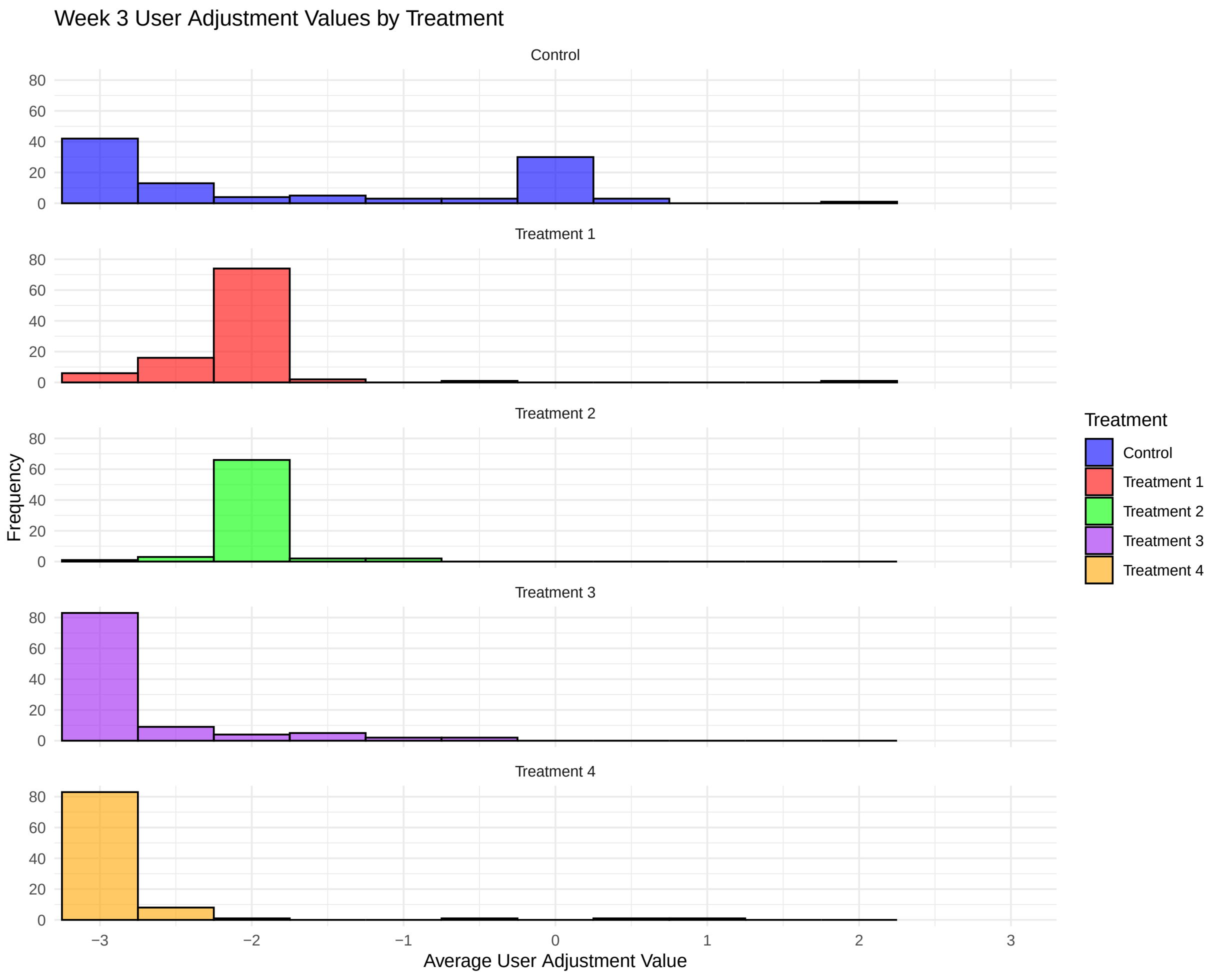
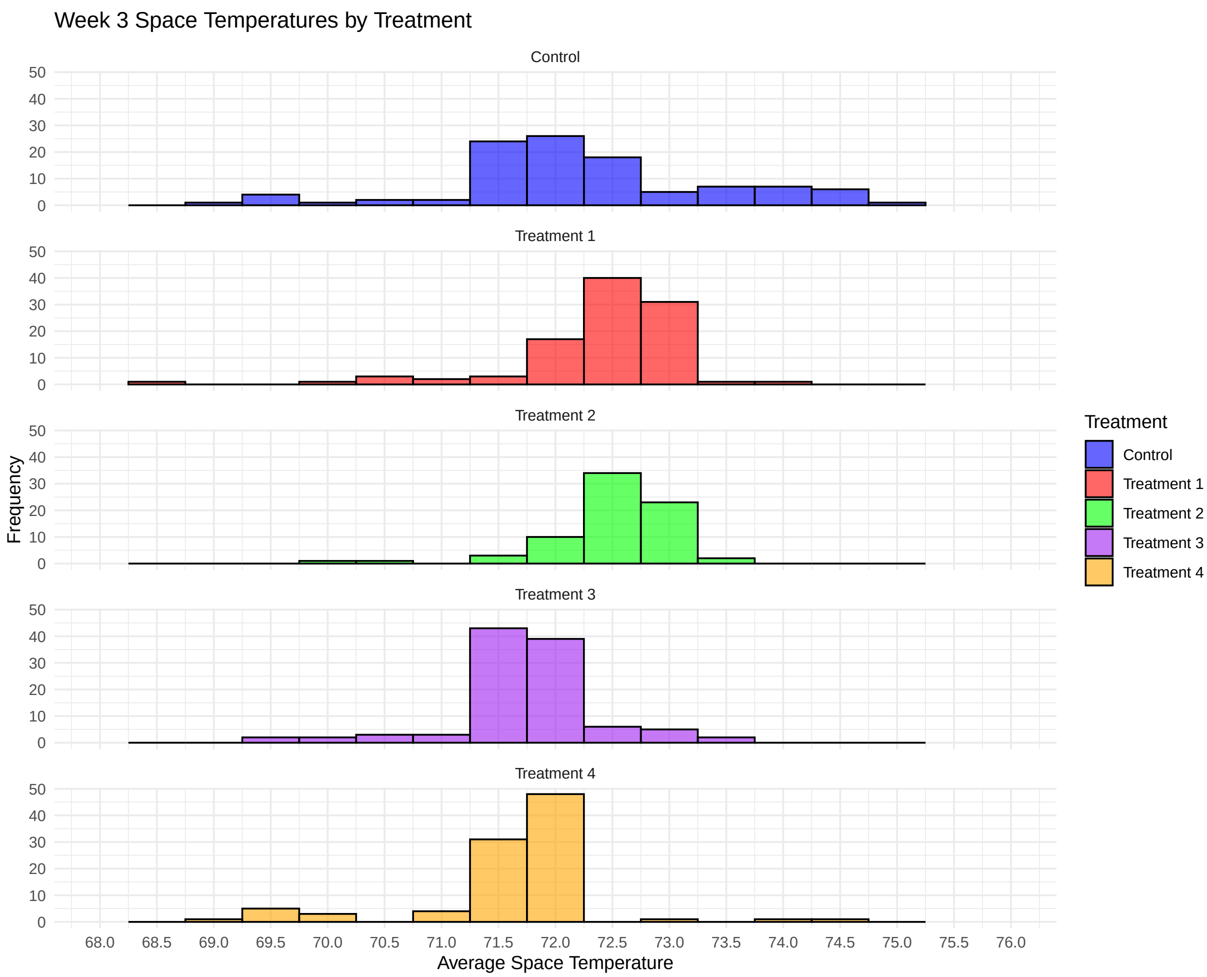
75.0
75.5
76.0



Week 3 User Adjustment Values by Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
Frequency
Average User Adjustment Value
Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4


Week 3 Space Temperatures by Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
Frequency
Average Space Temperature
Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
0
10
20
30
40
50
68.0
68.5
69.0
69.5
70.0
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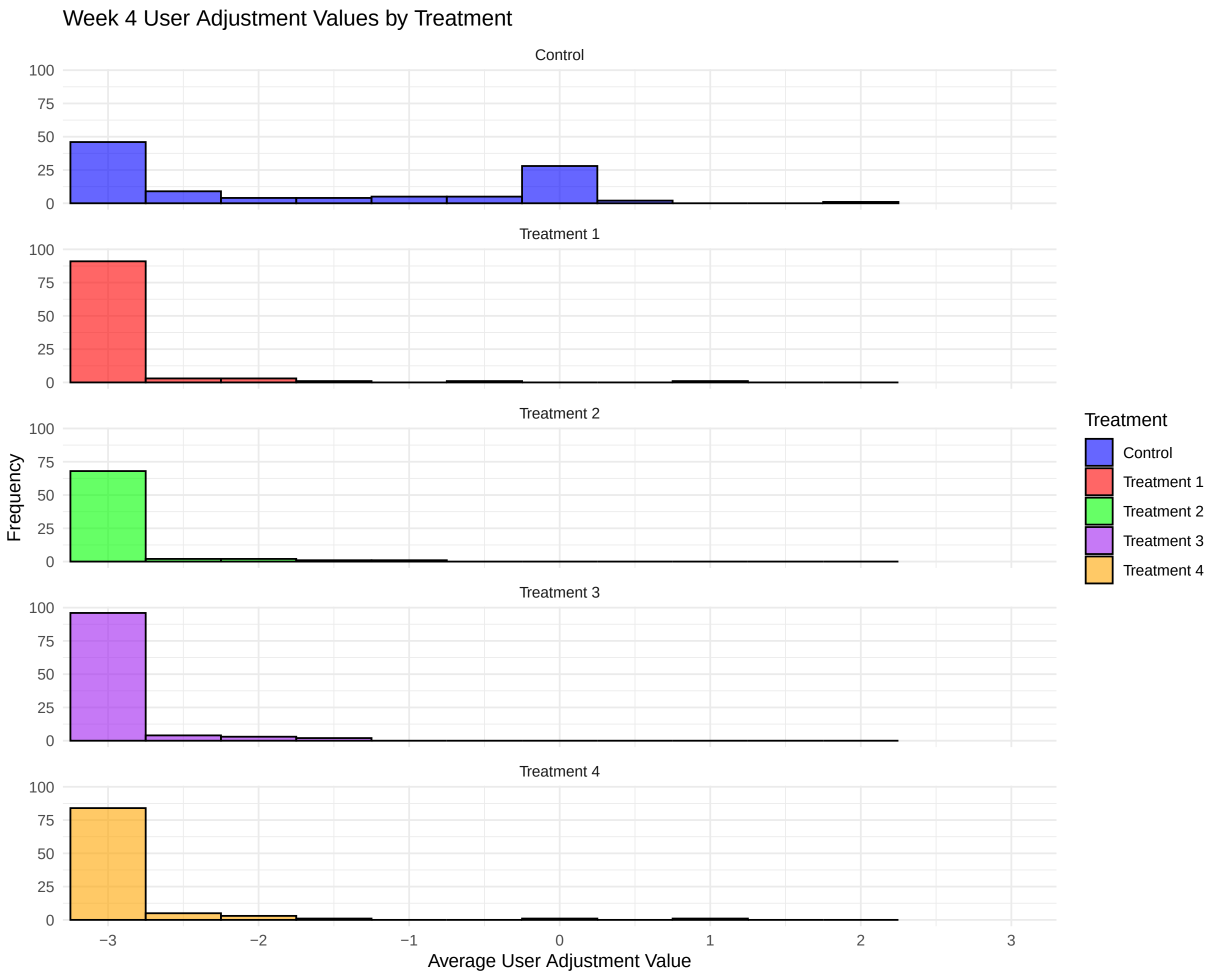
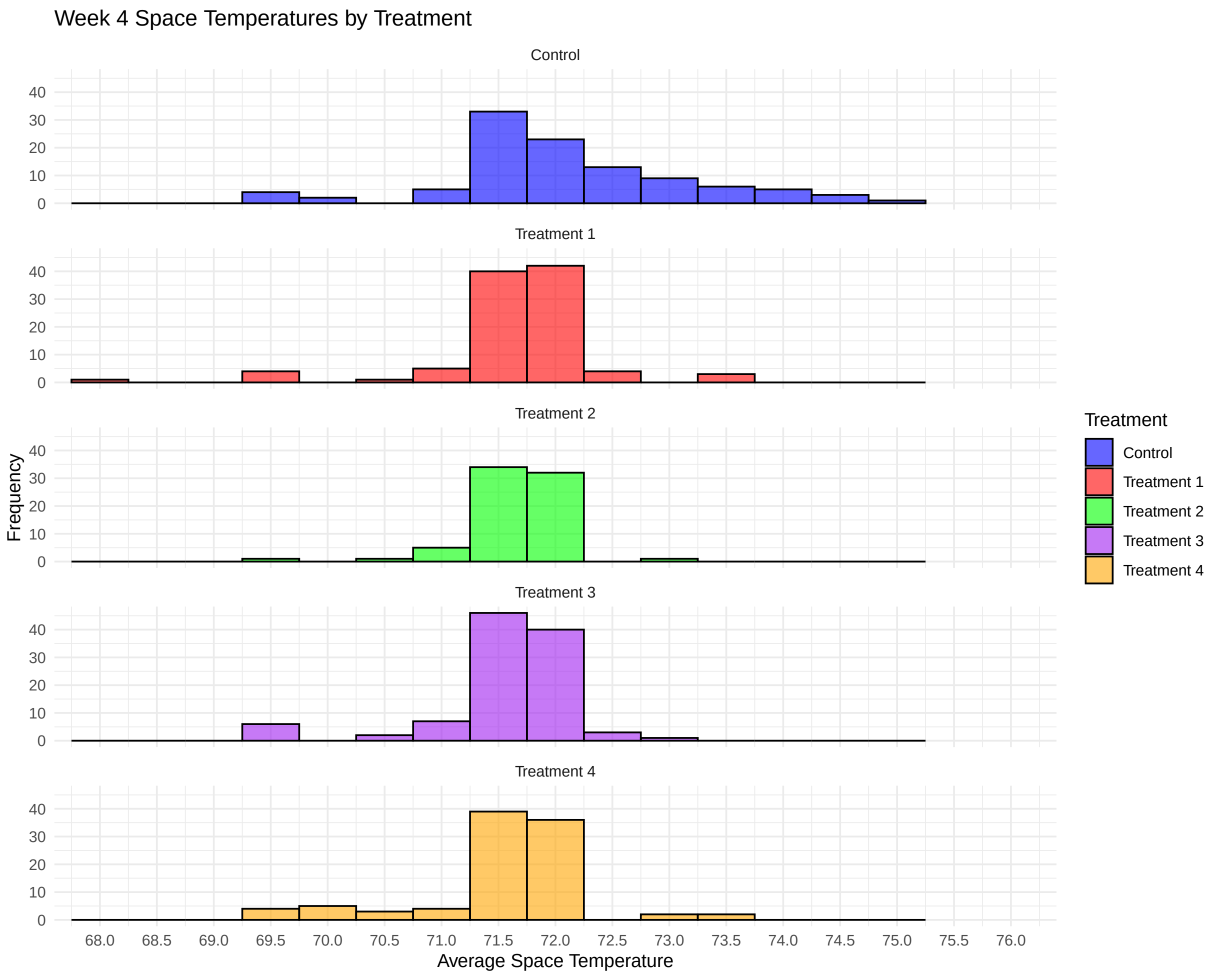
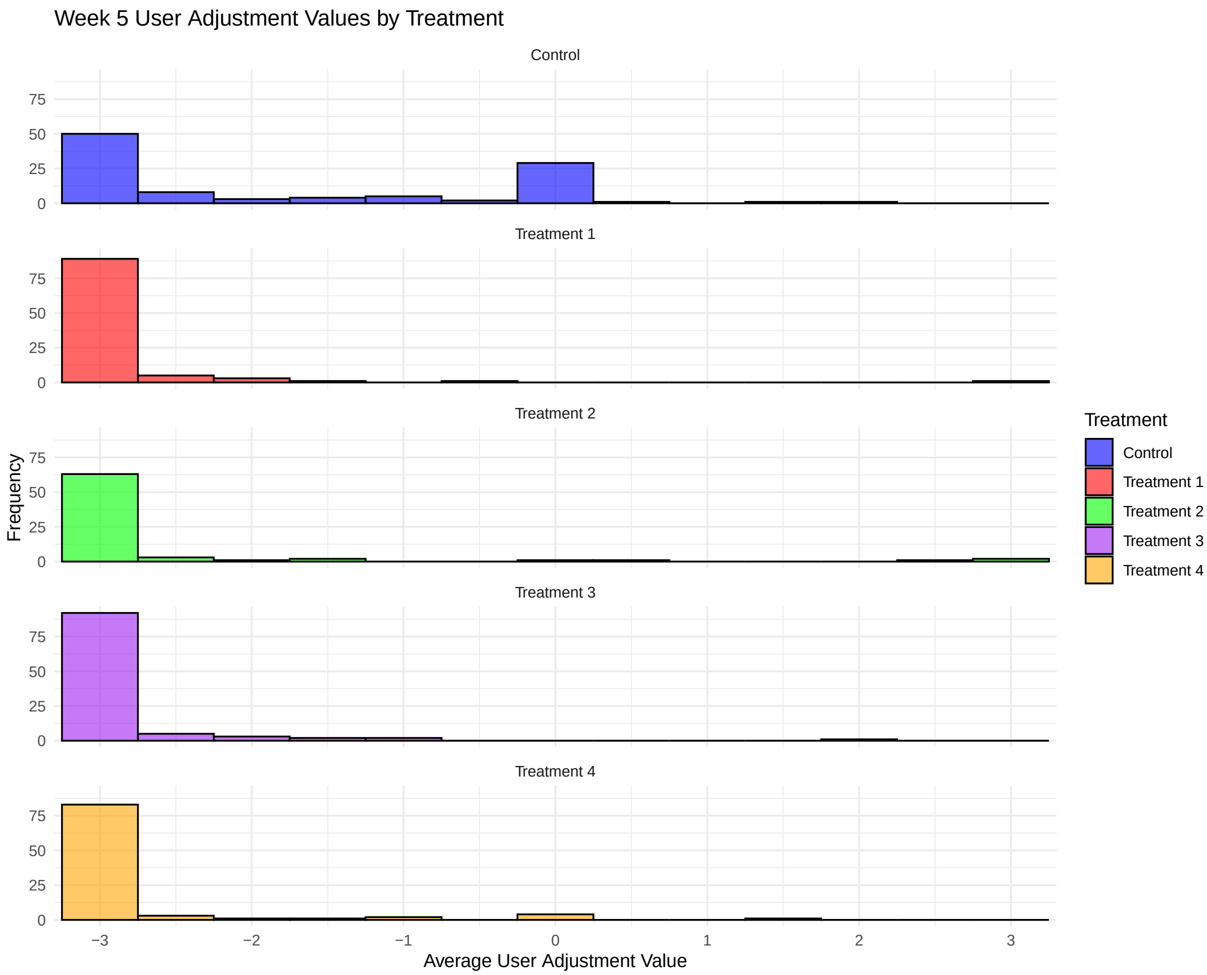
75.0
75.5
76.0

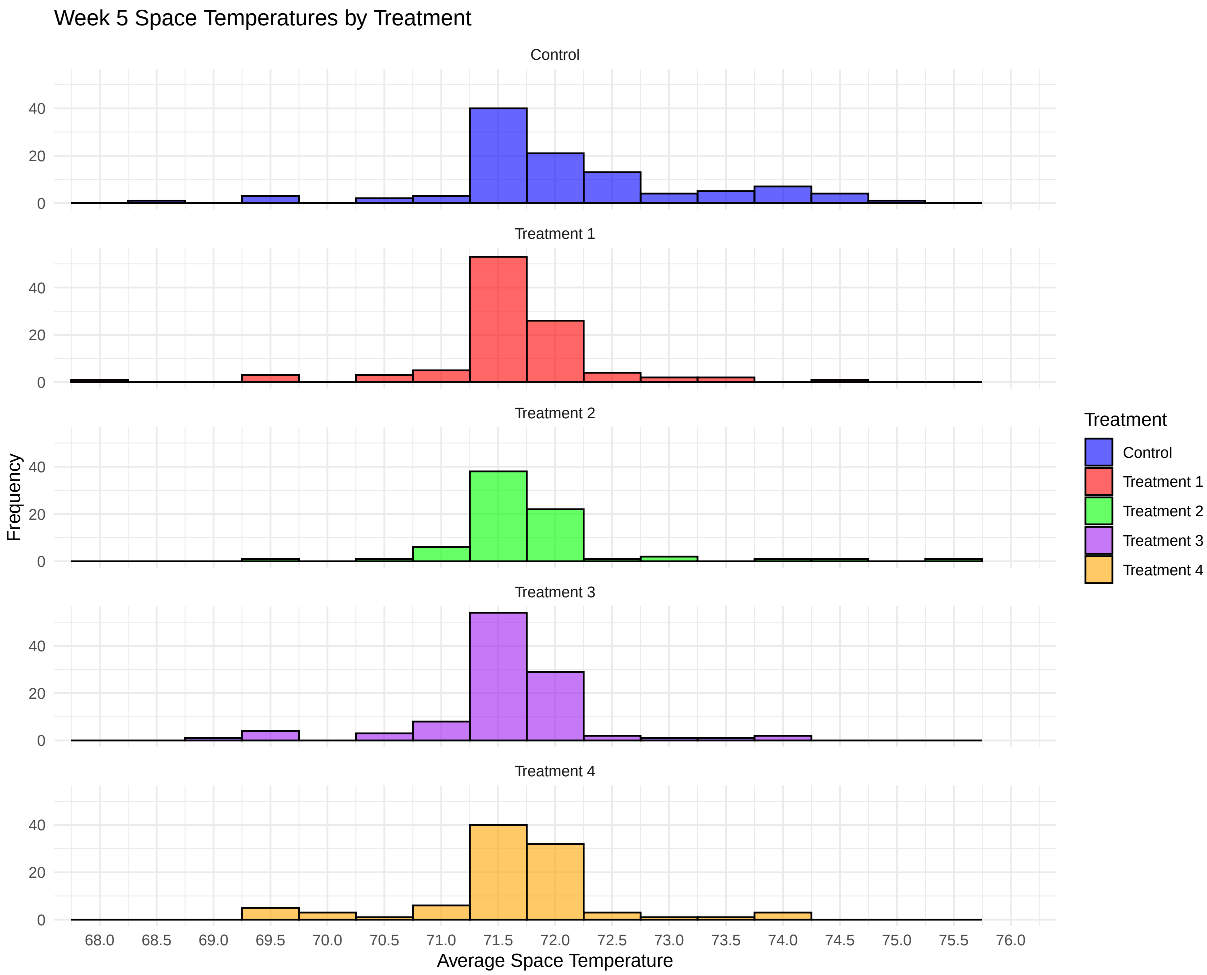


Week 4 User Adjustment Values by Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
100
75
50
25
0
Frequency
−3
−2
−1
0
1
2
3
Average User Adjustment Value
Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4

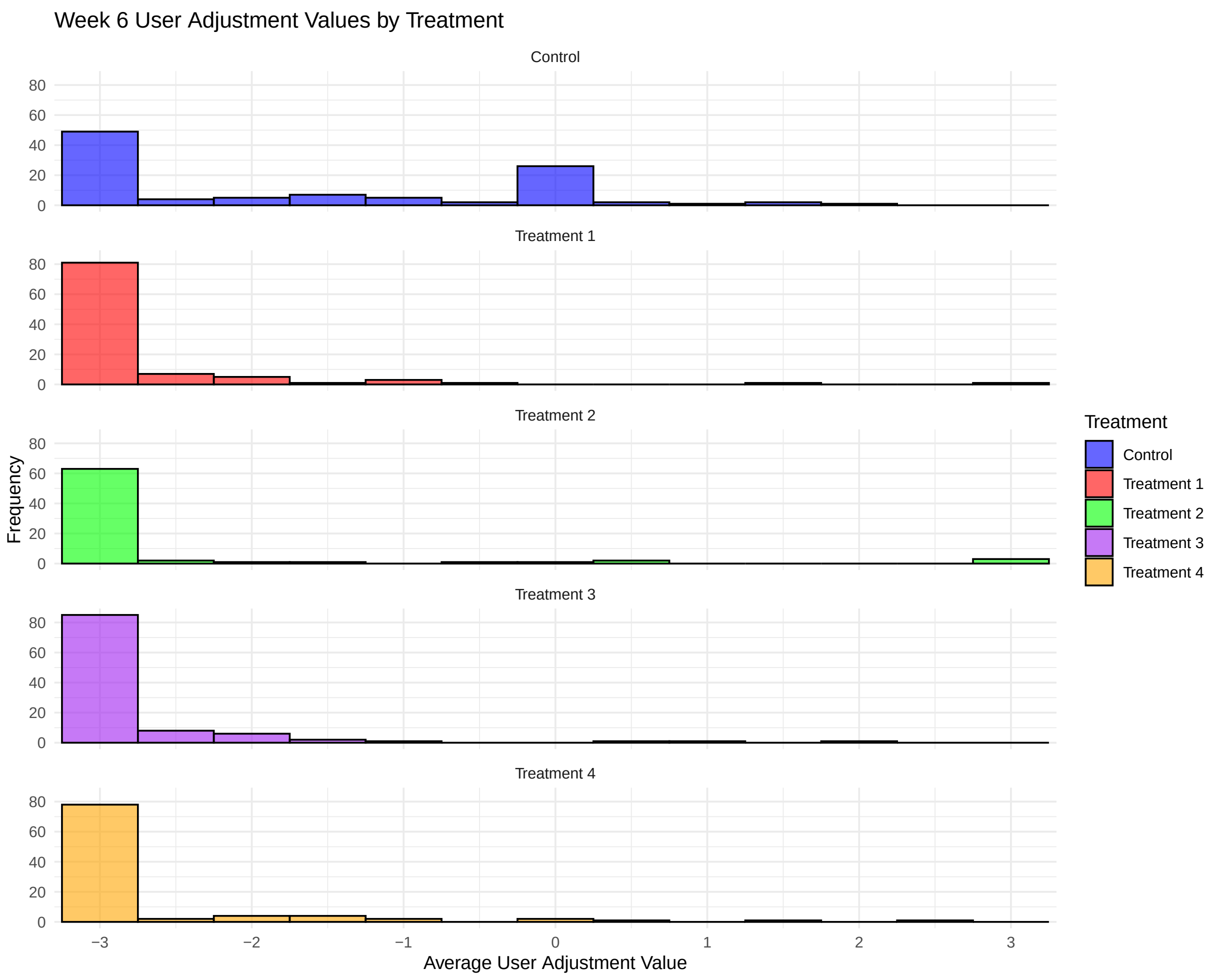

Week 4 Space Temperatures by Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
Frequency
Average Space Temperature
Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
0
10
20
30
40
68.0
68.5
69.0
69.5
70.0
70.5
71.0
71.5
72.0
72.5
73.0
73.5
74.0
74.5
75.0
75.5
76.0

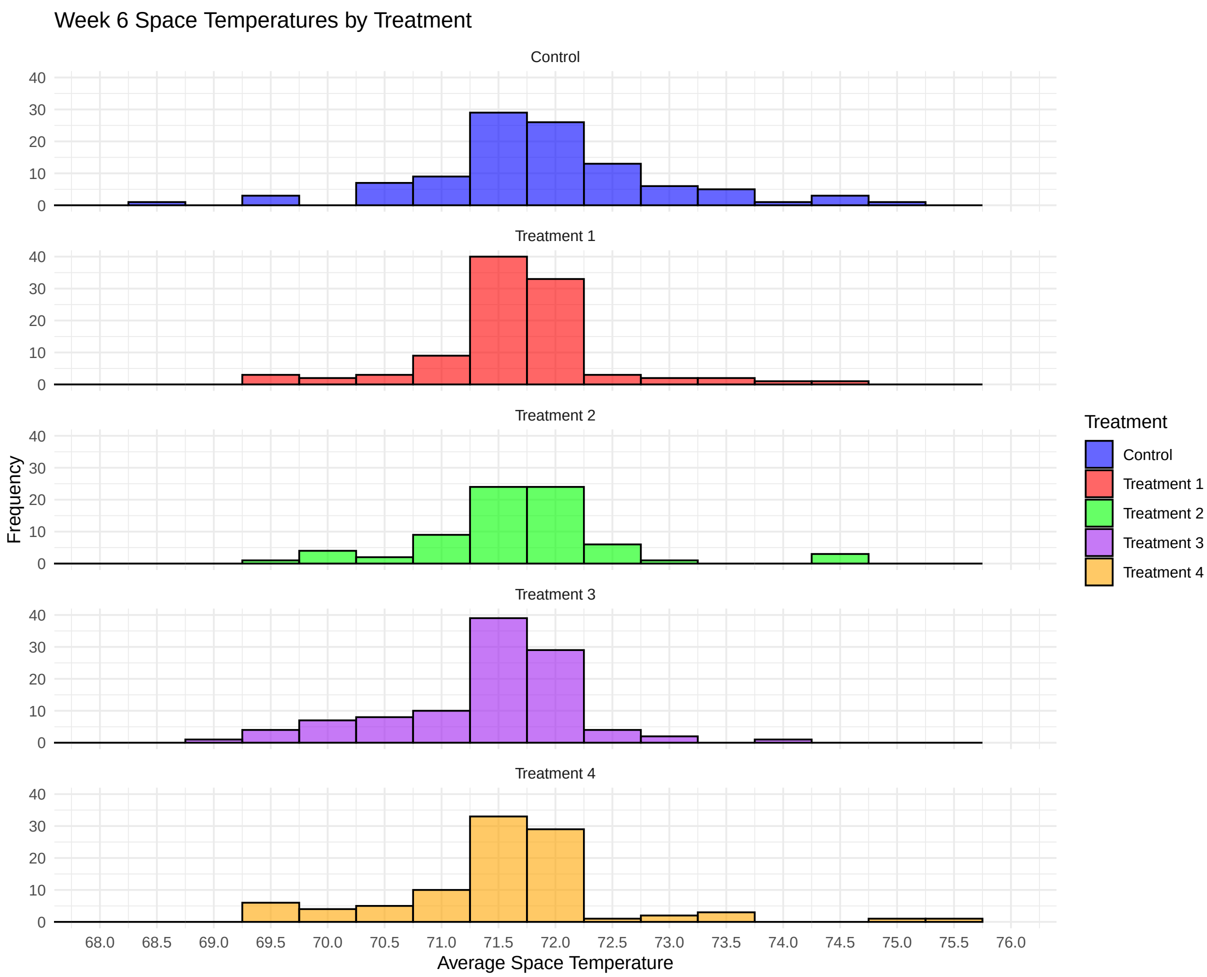


Week 5 User Adjustment Values by Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
Frequency
Average User Adjustment Value
Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4



Week 5 Space Temperatures by Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
Frequency
0
20
40
68.0
68.5
69.0
69.5
70.0
70.5
71.0
71.5
72.0
72.5
73.0
73.5
74.0
74.5
75.0
75.5
76.0
Average Space Temperature
Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4


Week 6 User Adjustment Values by Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
Frequency
80
60
40
20
0
−3
−2
−1
0
1
2
3
Average User Adjustment Value
Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4


Week 6 Space Temperatures by Treatment
Control
Treatment 1
Treatment 2
Treatment 3
Treatment 4
Frequency
Average Space Temperature
Treatment

A.2 IRB Exemption Letter

Institutional Review Board
210H Hullihen Hall
Newark, DE 19716
Phone: 302-831-2137
Fax: 302-831-2828

DATE: January 13, 2025

TO: Carl Nelson-Poteet
FROM: University of Delaware IRB

STUDY TITLE: [2158907-4] Residence Hall Energy Study
SUBMISSION TYPE: Amendment/Modification

ACTION: DETERMINATION OF EXEMPT STATUS
EFFECTIVE DATE: January 13, 2025

REVIEW CATEGORY: Exemption category # 2*(i)*

Thank you for your Amendment/Modification submission to the University of Delaware Institutional Review Board (UD IRB). According to the pertinent regulations, the UD IRB has determined this project is EXEMPT from most federal policy requirements for the protection of human subjects. The privacy of subjects and the confidentiality of participants must be safeguarded as prescribed in the reviewed protocol form.

This exempt determination is valid for the research study as described by the documents in this submission. Proposed revisions to previously approved procedures and documents that may affect this exempt determination must be reviewed and approved by this office prior to initiation. The UD amendment form must be used to request the review of changes that may substantially change the study design or data collected.

Unanticipated problems and serious adverse events involving risk to participants must be reported to this office in a timely fashion according with the UD requirements for reportable events.

A copy of this correspondence will be kept on file by our office. If you have any questions, please contact the UD IRB Office at (302) 831-2137 or via email at hsrb-research@udel.edu. Please include the study title and reference number in all correspondence with this office.

Dorm Temp Survey - 2024F

Start of Block: Informed Consent

Q1 Welcome and thank you for agreeing to participate in this survey. The purpose of this survey is to inform a research thesis examining thermostat use in UD residence halls. The entire survey will take about 10 minutes to complete. You have a chance to win an Amazon e-gift card for completing the survey. One $100 card, two $50 cards, and four $25 cards will be distributed. All of your survey responses will be treated anonymously. The only identifying information we will collect is your room number. If you chose to enter the raffle for one of the e-gift cards at the end of the survey, your email address will not be connected to your survey responses. Taking part in this survey is voluntary. You do not have to participate in this survey. If you choose to take part, you have the right to stop at any time. If you decide to not participate or if you decide to stop taking part in the survey at any time, there will be no penalty or loss of benefits to which you are otherwise entitled. Your decision to stop participation will not influence your current or future relationships with the University of Delaware. This project has been approved by the Institutional Review Board at the University of Delaware that oversees research involving human participants. There are no greater risks from participating in this study than those you would face during daily life. By continuing onto the next page, you provide your consent to be a participant in this survey. If you have any questions or concerns, please contact the Principal Investigator, Carl Nelson-Poteet at cnelsonp@udel.edu. You may also contact the University of Delaware Institutional Review Board at hsrb-research@udel.edu or (302) 831-2137. To consent to participate in this study, please click the “I agree” button below. If you do not consent, please click on the “Exit” button.

○ I Agree (1)

○ Exit (2)

End of Block: Informed Consent

Start of Block: Introducing Study

Q38 Before the survey begins, we will briefly describe the study that took place in your residence hall this past month. This study tested whether small changes to the default set temperature schedule in dorm rooms with adjustable thermostats can save energy. When indoor temperatures are closer to outdoor temperatures, heating/cooling systems can conserve energy. This in turn benefits the environment. This study took place over the month of October (September 30th through November 1st). During this period, the default set temperature schedule of some dorm rooms were remotely adjusted to be closer to the outdoor temperature. Not all dorm rooms were affected, meaning some rooms' temperature settings were not changed. When remote adjustments were made, they temporarily overrode the temperature that the room had previously been set to. However, occupants retained full control over the room thermostat and could adjust the room temperature as desired. This study did not eliminate or restrict the ability of people to change the temperature back. Select "Continue" to advance.

○ Continue (1)

End of Block: Introducing Study

Start of Block: Initial Reaction to Study

Q40 Last Spring, were you informed of being involved in a similar study?

○ Yes (1)

○ No (2)

○ No, but I knew a similar study took place last Spring (3)

○ Not sure (4)

Q28 Recall that not every dorm room was a part of this study. Based on your experiences this past month, do you believe that your dorm room was included? In other words, do you think your dorm room experienced changes to the default set temperature schedule?

○ Yes (1)

○ No (2)

○ I don't know (3)

Q30 How do you believe this study personally impacted you?

- ◯ I was strongly positively impacted (15)
- ◯ I was somewhat positively impacted (16)
- ◯ I have no strong feelings about how I was impacted (17)
- ◯ I was somewhat negatively impacted (18)
- ◯ I was strongly negatively impacted (19)
- ◯ I do not believe I was impacted at all (20)

Q29 At any point this past month, did you submit any official complaint (for example, a FixIt Request Form) regarding your dorm room's temperature?

- ◯ Yes (1)
- ◯ No (2)

Page Break

Q2 Overall, I would describe my thoughts toward this study as...

- ○ Extremely negative (1)
- ○ Somewhat negative (2)
- ○ Neither positive nor negative (3)
- ○ Somewhat positive (4)
- ○ Extremely positive (5)

Q3 Please indicate how much you agree with each of the following statements. This study...

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
...is important for understanding how to conserve energy (9)	○	○	○	○	○
...tried to make decisions for me (7)	○	○	○	○	○
...had a positive impact on the environment (5)	○	○	○	○	○
...tried to manipulate me (8)	○	○	○	○	○

Q31 Do you feel the potential benefits (possible energy conservation) of this study outweigh the potential costs (possible uncomfortable temperatures)

- ◯ The benefits are significantly greater (1)
- ◯ The benefits are somewhat greater (2)
- ◯ The benefits and costs are about the same (3)
- ◯ The costs are somewhat greater (4)
- ◯ The costs are significantly greater (5)

Display this question:

If Please indicate how much you agree with each of the following statements. This study... = ...had a positive impact on the environment [Somewhat disagree]

Or Please indicate how much you agree with each of the following statements. This study... = ...had a positive impact on the environment [Strongly disagree]

And If

Please indicate how much you agree with each of the following statements. This study... = ...is important for understanding how to conserve energy [Somewhat agree]

Or Please indicate how much you agree with each of the following statements. This study... = ...is important for understanding how to conserve energy [Strongly agree]

Q36 You indicated that this study is important for understanding how to conserve energy, but did not make a positive impact on the environment. Which of the following explanations best explain why you feel this way [select all that apply].

- ▢ I do not believe conserving energy has a positive impact on the environment (2)
- ▢ I do not believe enough dorm rooms stayed at the energy-saving temperatures to meaningfully benefit the environment (3)
- ▢ Even if all dorm rooms stayed at the energy-saving temperatures, I do not believe the positive impacts of this study are large enough to meaningfully benefit the environment (1)
- ▢ Other (4) ____

End of Block: Initial Reaction to Study

Start of Block: Session-Specific Reactance

Q32 The study that ran this month made the default set temperature schedule slightly colder, as the average outdoor temperature during this time was ~60 degrees. Which of the following emotions did this study make you feel? Select all that apply.

- ▢ Amused (1)
- ▢ Annoyed (2)
- ▢ Confused (3)
- ▢ Curious (4)
- ▢ Other(s) (5) ____
- ▢ I felt no emotions about this study (6)
- ▢ I do not recall (7)

End of Block: Session-Specific Reactance

Start of Block: WTA

Q34 Suppose that you will be living in a dorm room next year. Imagine you were offered *$10*, in exchange for your room being enrolled in this study next year. If you say yes, you would receive *$10* and your room would experience changes to the default set temperature schedule. If you say no, you would not receive *$10* and your room would not experience changes to the default set temperature schedule. Would you agree to it? It is very important to treat this question as a real decision you are making. Please respond as you would if you faced this choice in real life.

- ○ Yes, I would accept the $10 (6)
- ○ No, I would not accept the $10 (7)

Display this question:

If Suppose that you will be living in a dorm room next year. Imagine you were offered $10, in exchan... = Yes, I would accept the $10

Q23 Imagine you were instead offered *$5*, in exchange for your room being enrolled in this study next year. If you say yes, you would receive *$5* and your room would experience changes to the default set temperature schedule. If you say no, you would not receive *$5* and your room would not experience changes to the default set temperature schedule. Would you agree to it? It is very important to treat this question as a real decision you are making. Please respond as you would if you faced this choice in real life.

- ◯ Yes, I would accept the $5 (6)
- ◯ No, I would not accept the $5 (7)

Display this question:

If Suppose that you will be living in a dorm room next year. Imagine you were offered $10, in exchan... = No, I would not accept the $10

Q38 Imagine you were instead offered *$25*, in exchange for your room being enrolled in this study next year. If you say yes, you would receive *$25* and your room would experience changes to the default set temperature schedule. If you say no, you would not receive *$25* and your room would not experience changes to the default set temperature schedule. Would you agree to it? It is very important to treat this question as a real decision you are making. Please respond as you would if you faced this choice in real life.

- ◯ Yes, I would accept the $25 (6)
- ◯ No, I would not accept the $25 (7)

End of Block: WTA

Start of Block: Possible Explanations - Dorm Rooms

Q12 Before this survey, did you know how to adjust the temperature of your dorm room?

- ◯ Yes (1)
- ◯ No (2)

Q34 Do you believe your thermostat is functioning correctly?

- ◯ Yes (1)
- ◯ No (2)
- ◯ Unsure - I have used it but am not sure if it functions correctly (3)
- ◯ Unsure - I have never used it (4)

Q14 How often do you change the temperature of your dorm room?

- ◯ More than once a day (1)
- ◯ About once a day (2)
- ◯ A few times a week (3)
- ◯ About once a week (4)
- ◯ Less than once a week (5)
- ◯ Never (6)
- ◯ Other (7) ____

Q35 If it were easier to adjust the temperature of your dorm room (for example, through an app or remote control), do you think you would adjust the temperature more frequently?

- ◯ I would adjust temperatures significantly more frequently (1)
- ◯ I would adjust temperatures a little bit more frequently (2)
- ◯ I would not adjust temperatures more frequently (3)

Page Break

Q15 How much do you agree with the following statement: I view the default set temperature of my dorm room thermostat as the recommended temperature for my room

○ Strongly agree (1)

○ Somewhat agree (2)

○ Neither agree nor disagree (3)

○ Somewhat disagree (4)

○ Strongly disagree (5)

Q16 Other than comfort, do any of the following factors influence your decision on whether or not to adjust your dorm room temperature? Check all that apply

▢ Roommate's or guest's comfort (1)

▢ Effort required to change the temperature (2)

▢ Environmental impacts of heating/cooling (3)

▢ Length of time you plan to be in the room (4)

▢ Other (5) ____

▢ No other factors influence my decision (6)

Q32 In the past month, have you used a plug-in fan in your dorm room, or a similar device that cools you down?

○ Yes (1)

○ No (2)

Q33 In the past month, have you used a space heater in your dorm room, or a similar device that warms you up?

○ Yes (1)

○ No (2)

Page Break

Q39 When you are in your dorm room, how frequently do you leave your door/window open?

○ Never/Almost Never (1)

○ Occasionally (2)

○ About half the time (3)

○ Most of the time (4)

Q37 When you change your dorm room's temperature, approximately how long (in minutes/hours) do you think it takes for your room to get to that set temperature?

○ Less than 1 hour (7)

○ 1 to 2 hours (8)

○ 2 to 3 hours (13)

○ More than 3 hours (14)

○ I don't know (15)

○ Other (16) ____

End of Block: Possible Explanations - Dorm Rooms

Start of Block: Possible Explanations - Non Dorm Rooms

Q18 Before this survey, did you know how to adjust the temperature of communal rooms in your residence hall (lounges, study rooms, etc.)?

○ Yes (1)

○ No (2)

Q20 How often do you change the temperature of communal rooms in your residence hall (lounges, study rooms, etc.)?

- ◯ More than once a day (1)
- ◯ About once a day (2)
- ◯ A few times a week (3)
- ◯ About once a week (4)
- ◯ Less than once a week (5)
- ◯ Never (6)
- ◯ Other (7) ____

Q36 If it were easier to adjust the temperature of of communal rooms in your residence hall (for example, through an app or remote control), do you think you would adjust the temperature more frequently?

- ◯ I would adjust temperatures significantly more frequently (1)
- ◯ I would adjust temperatures a little bit more frequently (2)
- ◯ I would not adjust temperatures more frequently (3)

Q21 How much do you agree with the following statement: I viewed the original temperature of the communal rooms' thermostats in my residence hall (lounges, study rooms, etc.) as the recommended temperature for the room

- ○ Strongly agree (1)
- ○ Somewhat agree (2)
- ○ Neither agree nor disagree (3)
- ○ Somewhat disagree (4)
- ○ Strongly disagree (5)

Q34 Other than comfort, do any of the following factors influence your decision on whether or not to adjust the communal rooms' (lounges, study rooms, etc.) temperature? Check all that apply

- ▢ Other people's comfort (1)
- ▢ Effort required to change the temperature (2)
- ▢ Environmental impacts of heating/cooling (3)
- ▢ Length of time you plan to be in the room (4)
- ▢ Other (5) ____
- ▢ No other factors influence my decision (6)

End of Block: Possible Explanations - Non Dorm Rooms

Start of Block: Occupancy

Q37 Which of the following best describes your gender?

- ○ Male (1)
- ○ Female (2)
- ○ Non-Binary (3)
- ○ Prefer Not to Say (4)

Q5 Which Residence Hall do you live in?

▼ Caeser Rodney A (4) ... Other (9)

Q6 What is your dorm room number?

____

Q28 How many people live in your dorm room (including you)?

- ○ 1 (1)
- ○ 2 (2)
- ○ 3 (3)
- ○ Other (4) ____

Q25 Select the hours you are usually in your dorm room on each of the following days:

	Morning (8am - 11am) (1)	Midday (11am - 1pm) (2)	Afternoon (1pm - 5pm) (3)	Evening (5pm - 10pm) (4)	Night (10pm - 8am) (5)	I do not have a consistent schedule (6)	I am not in the room on this day (7)
Monday (1)	▢	▢	▢	▢	▢	▢	▢
Tuesday (2)	▢	▢	▢	▢	▢	▢	▢
Wednesday (3)	▢	▢	▢	▢	▢	▢	▢
Thursday (4)	▢	▢	▢	▢	▢	▢	▢
Friday (5)	▢	▢	▢	▢	▢	▢	▢
Saturday (6)	▢	▢	▢	▢	▢	▢	▢
Sunday (7)	▢	▢	▢	▢	▢	▢	▢

Q36 Select the hours someone (you or your roommate) is usually in your dorm room on each of the following days:

	Morning (8am - 11am) (1)	Midday (11am - 1pm) (2)	Afternoon (1pm - 5pm) (3)	Evening (5pm - 10pm) (4)	Night (10pm - 8am) (5)	We do not have a consistent schedule (6)	We are not in the room on this day (7)
Monday (1)	▢	▢	▢	▢	▢	▢	▢
Tuesday (2)	▢	▢	▢	▢	▢	▢	▢
Wednesday (3)	▢	▢	▢	▢	▢	▢	▢
Thursday (4)	▢	▢	▢	▢	▢	▢	▢
Friday (5)	▢	▢	▢	▢	▢	▢	▢
Saturday (6)	▢	▢	▢	▢	▢	▢	▢
Sunday (7)	▢	▢	▢	▢	▢	▢	▢

Q41 How frequently does your dorm room have 5 or more people in it?

- ○ Very Frequently (1)
- ○ Somewhat Frequently (2)
- ○ Not Frequently (3)
- ○ Not at All (4)

Q38 Are there any last comments you would like to share regarding this topic?

____

End of Block: Occupancy

Start of Block: Raffle

Q27 As a thank you for participating in this survey, we would like to offer you a chance to enter a prize drawing to win an Amazon e-gift card. Possible prizes include a $100 card, a $50 card, and a $25 card. If you wish to enter the drawing, we will need to collect your email address to inform you of the result. Your email address will not be used for any other reason, and will not be linked with the other responses in this survey. Would you like to enter the prize drawing?

- ○ Yes (1)
- ○ No (2)

End of Block: Raffle

A.3 Descriptive Statistics

Table A.1: Week 0

Treatment	ST_avg	ST_ADJ_avg	ST_s.d	ST_Min	ST_Max	ADJ_s.d	ADJ_Min	ADJ_Max
Control	73.03	-0.86	1.17	69.38	74.94	1.28	-3.00	1.50
T1	73.16	-1.04	1.18	70.10	74.79	1.27	-3.00	0.00
T2	73.48	-0.59	1.03	71.29	74.96	1.08	-3.00	0.72
T3	73.11	-1.03	1.07	71.63	74.86	1.26	-3.00	0.78
T4	73.07	-1.00	1.20	69.28	75.38	1.28	-3.00	1.88

Table A.2: Week 1

Treatment	ST_avg	ST_ADJ_avg	ST_s.d	ST_Min	ST_Max	ADJ_s.d	ADJ_Min	ADJ_Max
Control	72.47	-1.44	1.13	69.33	74.91	1.40	-3.00	2.00
T1	73.03	-1.01	1.15	68.92	74.93	1.26	-2.97	1.70
T2	73.45	-0.41	0.87	71.40	74.69	0.73	-2.48	1.74
T3	71.67	-2.83	0.56	69.52	73.21	0.50	-3.00	-0.03
T4	71.57	-2.86	0.78	68.82	73.54	0.47	-3.00	0.21

Table A.3: Week 2

Treatment	ST_avg	ST_ADJ_avg	ST_s.d	ST_Min	ST_Max	ADJ_s.d	ADJ_Min	ADJ_Max
Control	72.19	-1.59	1.10	68.92	74.64	1.46	-3.00	2.00
T1	72.58	-1.58	0.96	67.78	74.32	0.88	-2.97	2.82
T2	72.89	-1.13	0.78	70.92	73.97	0.53	-2.65	1.33
T3	71.66	-2.67	0.77	69.34	74.18	0.88	-3.00	2.77
T4	71.48	-2.89	0.73	69.26	73.24	0.47	-3.00	0.82

Table A.4: Week 3

Treatment	ST_avg	ST_ADJ_avg	ST_s.d	ST_Min	ST_Max	ADJ_s.d	ADJ_Min	ADJ_Max
Control	72.22	-1.69	1.17	68.96	74.76	1.40	-3.00	2.00
T1	72.39	-2.08	0.73	68.61	74.11	0.52	-2.96	2.02
T2	72.49	-1.99	0.55	70.14	73.41	0.26	-2.81	-0.78
T3	71.72	-2.75	0.63	69.26	73.33	0.56	-3.00	-0.36
T4	71.59	-2.84	0.76	69.24	74.28	0.60	-3.00	0.83

Table A.5: Week 4

Treatment	ST_avg	ST_ADJ_avg	ST_s.d	ST_Min	ST_Max	ADJ_s.d	ADJ_Min	ADJ_Max
Control	72.10	-1.71	1.05	69.35	74.78	1.39	-3.00	2.00
T1	71.65	-2.86	0.71	67.99	73.40	0.52	-3.00	0.98
T2	71.65	-2.91	0.42	69.37	72.77	0.31	-3.00	-1.17
T3	71.54	-2.91	0.62	69.31	73.22	0.29	-3.00	-1.43
T4	71.53	-2.84	0.74	69.29	73.70	0.57	-3.00	1.16

Table A.6: Week 5

Treatment	ST_avg	ST_ADJ_avg	ST_s.d	ST_Min	ST_Max	ADJ_s.d	ADJ_Min	ADJ_Max
Control	72.07	-1.77	1.09	68.48	74.86	1.41	-3.00	2.00
T1	71.64	-2.85	0.77	67.85	74.29	0.69	-3.00	3.00
T2	71.77	-2.61	0.75	69.40	75.30	1.27	-3.00	3.00
T3	71.59	-2.83	0.69	69.25	74.04	0.61	-3.00	1.82
T4	71.60	-2.74	0.82	69.27	74.16	0.81	-3.00	1.68

Table A.7: Week 6

Treatment	ST_avg	ST_ADJ_avg	ST_s.d	ST_Min	ST_Max	ADJ_s.d	ADJ_Min	ADJ_Max
Control	71.85	-1.69	1.04	68.38	74.95	1.46	-3.00	2.00
T1	71.61	-2.71	0.87	67.23	74.33	0.88	-3.00	3.00
T2	71.68	-2.53	0.82	69.54	74.55	1.37	-3.00	3.00
T3	71.41	-2.73	0.78	69.22	74.15	0.77	-3.00	1.81
T4	71.50	-2.64	0.97	69.33	75.42	0.98	-3.00	2.63

A.4 Standard Heat Transfer Equation

Standard Heat Transfer Equation:

$$Q = m * C_p * \Delta T$$

Q is heat transfer rate (Btu/hr), m = mass flow rate (lb/hr), C(p) = Specific heat capacity (Btu/lb°F), delta T = Temperature difference (°F)

1 gallon of water is $\tilde{8}$.34 lbs, so m can be set equal to:

$$m = \frac{X_{gallons}}{minute} * \frac{60_{minute}}{hour} * \frac{8.34_{lbs}}{gallon}$$

Which simplifies to

$$m = \frac{X_{gallon}}{minute} * \frac{500.4_{lbs,minute}}{1gallon, hr}$$

Once a value is given for GPM, units will simplify to lbs/hr.

For Water, C(p) is equal to 1 Btu/lb°F

Units in full equation cancel to BTU/hr.