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USING ALGORITHMIC NUDGES TO SAVE ENERGY AND WATER: A PROPOSAL FOR A LONGITUDINAL FIELD EXPERIMENT

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Research in Progress

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Abstract

Energy and water consumption are significant sources of greenhouse gas emissions. While facilitating conservation behaviors in private households can help to mitigate these emissions, the effects of such mitigations are often indirect and delayed. Presenting meaningful feedback about consumption can help to make clear the positive effects of conservation behaviors to those who undertake them. We propose a large-scale field experiment to increase energy and water conservation through algorithmic eco-nudges. We use smart metering data to provide transparency, social references, and information about the environmental effects of conservation behavior. The proposed research is planned in a longitudinal design for 8 weeks in the winter of 2022/23 in Germany. The findings are expected to contribute to scholarly research on nudging and practice as well as to housing providers and policymakers who are interested in green nudging.

Keywords: Algorithm, Nudge, Pro-environmental Behavior, Field Experiment, Longitudinal.

1 Introduction

The harmful consequences of the climate crisis to communities around the globe, along with imminent energy shortages and skyrocketing gas prices in Europe, underscore the importance of economizing in the use of resources like energy and water. The current circumstances disproportionately affect and are affected by private households because of increasing ancillary costs and households' ongoing contribution to greenhouse gas emissions (Hertwich & Peters, 2009). Heating alone accounts for more than half of private household energy emissions in Germany (Statistisches Bundesamt, 2021). Therefore, finding ways to decrease energy and water consumption and the resulting environmental footprint of private households can be of significant societal value.

Scholarly research indicates that technology can encourage pro-environmental behaviors (PEBs). For example, incorporating goal-setting and feedback in a web portal has been used successfully in efforts to conserve electricity (Loock et al., 2013) and in fostering online discussions on an organization's intranet about sustainable printing practices to save paper (Degirmenci & Recker, 2023).

Many studies rely on the concept of nudging to induce individuals to engage in PEBs (e.g., Degirmenci & Recker, 2023). Nudges are elements of (online) choice environments that rely on psychological effects to steer decisions and behaviors in a predefined way (Thaler & Sunstein, 2008; Weinmann et al., 2016). For example, real-time digital feedback on water consumption encouraged individuals to adopt more sustainable showering habits (Tiefenbeck et al., 2018), and framing vegetarian food options as beneficial to personal and planetary health in an online setting shifted consumer preferences toward vegetarian dishes (Shreedar & Galizzi, 2021).

While simplicity has been a central property of digital nudges, primarily for pragmatic reasons like implementation costs (Schneider et al., 2018), recent technological advances afford new potential for personalization and contextualization (Mele et al., 2021; Möhlmann, 2021). Behavioral interventions can rely on more data (and more accurate data) that is relevant to the individuals targeted and suitable to the circumstances. For example, wearable self-tracking devices can improve health-related behaviors by providing users with personalized behavioral recommendations and cues based on detailed behavioral monitoring data about the individual (Rieder et al., 2021). Similarly, Buckley (2020) shows that smart meters that generate individual data can provide individuals with meaningful information and recommendations related to their consumption and that personalized advice and real-time feedback on energy consumption are superior to feedback about electricity costs and general savings advice.

However, which design elements and underlying psychological mechanisms are most effective in guiding PEB in digital environments remains unclear. Nudges that rely on rich data and sophisticated data analytics and can be adapted to certain target groups and contexts are called *algorithmic nudges* (Möhlmann, 2021) or *smart nudges* (Mele et al., 2021). As the literature on algorithmic nudging is scarce, we aim to explore their potential in the domain of PEB, specifically energy and water conservation. Our research question asks: *Are algorithmic nudges effective in encouraging individuals' PEBs?*

To address the research question, we designed three nudges based on daily smart meter data with differing degrees of "smartness" (i.e., pure consumption, eco-score, CO_2 emissions) to be displayed in a mobile application for apartment tenants. We propose a longitudinal field experiment over 8 weeks to target a population of around 1,500 tenants in Germany. Our study aims to shed light on the differential effects of non-algorithmic nudging (i.e., consumption) versus algorithmic nudging (i.e., "eco-score" and "eco-score plus"). We expect to contribute to the nudging literature by expanding the narrow and simplistic definition of *digital nudges* to include the contemporary aspect of algorithms and to inform the future design of nudges and policymaking in the sustainability domain.

2 Background

2.1 Algorithmic Nudging

Nudges are elements of choice architecture that influence behavior in a predetermined way (Thaler & Sunstein, 2008). They do not provide financial incentives or ban options but use psychological mechanisms like social reference and loss aversion to influence decision-making (Thaler & Sunstein, 2008). Nudges direct choice using means like structural redesign of the environment by setting a default or personalized information in the form of social feedback (Beermann, Rieder, & Uebernickel, 2022). Nudges are increasingly applied in the digital sphere to shape users' behavior by manipulating the user interface's design elements (Weinmann et al., 2016). Popular applications of digital nudges are in electronic commerce (e.g., Dennis et al., 2020), software development (e.g., Haki et al., 2022), health (e.g., Capasso & Umbrello, 2022), and privacy (e.g., Almuhimedi et al., 2015).

The principle properties of nudges are that they are non-binding, easy to avoid (Hansen, 2016), and simple. In digital environments, only the user front end is relevant to nudging (Weinmann et al., 2016); anything that goes beyond the surface (Burton-Jones & Grange, 2013) requires backend capacity (e.g., data input, data analytics) and is not considered as part of the current definitions of a *digital nudge* (Weinmann et al., 2016). This distinction is valuable in the physical world, where altering the deep structure of an environment (e.g., the layout of a building) is more complicated than changing the surface (e.g., the furnishings of each room). However, in the digital sphere, recent developments in sensor technology, information-processing capacity, data analytics, internet bandwidth, and diffusion of mobile devices have facilitated applications' ability to go beyond the surface (Fill, 2020) and have given rise to the class of "smart" information systems (IS) (Rudas & Fodor. 2008). Leveraging more detailed data to make nudges more personalized and contextualized is becoming easier and cheaper, and using algorithms in the backend system can enhance nudges' effects (Mele et al., 2021). So-called *algorithmic nudges* use algorithms to harness the ubiquitous data that is available (Möhlmann, 2021). Algorithms evolve the choice architecture's characteristics from static to dynamic by adjusting to personalized and contextualized input variables.

Algorithms can convert raw data into meaningful information such that accuracy and personalization make the content meaningful and valuable not only in supporting decision-making in complex environments (e.g., Haki et al., 2022) and but also in facilitating behavior change (e.g., Tyler et al., 2020). Whereas positive behavioral outcomes cannot be expected if the user does not perceive a nudge's information as relevant and valuable (Čaić et al., 2019), a fit between the nudge and personal characteristics can lead to significant outcomes. For example, Matz et al. (2071) find that matching an advertisement to participants' psychological preferences leads to significantly more clicks and 50 percent more purchases than mismatching the advertising does. Moreover, data-driven nudges can support sensemaking (i.e., the process of attributing meaning) about sustainable behavior (Degirmenci & Recker, 2016). For example, Degirmenci and Recker (2023) and Seidel et al. (2013) find that reflective disclosure helps individuals gain insights into their consumption behavior and reduces the amount of paper used for printing. The process of individual sensemaking is described as an antecedent to PEB (Degirmenci & Recker, 2016), but IS research lacks detailed information about how algorithms in the domain of environmental sustainability can support sensemaking as it relates to PEBs. Currently, most nudge applications for PEBs use IS's static, rather than dynamic, capabilities. Our proposed research will tap the potential for algorithmic nudges to boost environmental sensemaking.

2.2 Pro-Environmental Behavior and Sensemaking

PEBs like choosing a bike ride over a car ride to minimize greenhouse gases can help to minimize the ecological impact of human decisions, behaviors, and business activity (Krajhanzl, 2010). The positive outcomes of PEBs are distinct from those of other classes of behavior (Barton & Grüne-Yanoff, 2015), as PEB is pro-social and mainly benefits the common good, whereas so-called pro-self behaviors primarily benefit the individual. Pro-social behaviors may have disadvantages for the individual. For example, air travel is often faster and sometimes even cheaper than taking the train, but taking the train means fewer carbon emissions, benefitting society (e.g., Hilton et al., 2014). Given such disadvantages to the individual, scholars are interested in what motivates people cast personal benefits aside in favor of PEBs.

Melville (2010) postulates that decisions that lean toward sustainability follow the formation of pro-environmental beliefs and an intention to act, while Degirmenci and Recker (2023) and Seidel et al. (2013) propose that sensemaking influences belief formation and subsequent sustainable action. Sensemaking describes the attribution of meaning to the circumstances, which influences subsequent actions (Weick et al., 2005), so sensemaking can be described as transitive and ongoing. Seidel et al. (2013) investigate an IT company's transformation toward embracing sustainable practices (e.g., lowering printed papers) and shows how IS supported this process by offering functional affordances (e.g., dashboard to track printed papers). On an individual level, sensemaking about affordances allows individuals to understand their personal contributions to an overall sustainability goal (Seidel et al., 2013). Seidel et al. (2013) describe the properties of the IS that gives rise to sensemaking as *reflective disclosure* to monitor, analyze, and present relevant information about, for example, resource or energy consumption and *information democratization*, which manifest as accessibility and transparency related to the target goals. Seidel et al. (2018) also deduce four characteristics that IS should have to support sustainability transformations: (i) presentation of novel environmental information regarding facts, observations, or general behavior; (ii) the ability to store and categorize ideas; (iii) the ability to interact with other users (e.g., commenting or discussions); and (iv) features of action planning and feedback. These material properties support individuals and organizations in sensemaking about sustainability (Seidel et al., 2018).

As data becomes increasingly ubiquitous, algorithms play an essential role in the process of *reflective disclosure*. Algorithms are often implemented to automate data monitoring and analysis and to help individuals generate insights. However, individuals need to make sense of the information that the algorithm presents (Seidel et al., 2013). To enhance *algorithm sensemaking*, people need to understand how the algorithm operates and produces outcomes (Möhlmann et al., 2023). If the algorithm limits ambiguity, tells an accurate story about the data, and provides consistent access to outputs (Möhlmann et al., 2023), algorithmic nudges can provide individuals with the personalized and contextualized information they need to make informed decisions.

Intentions and behavior are closely related (Ajzen, 1991), but only one in ten pro-environmental intentions leads to actual PEB (Klöckner, 2013). Nudges have been shown to be successful in bridging the *intention-behavior gap* in a non-obtrusive way (Mertens et al., 2022). In the academic literature, a variety of types of nudges (e.g., feedback, reminders, defaults) demonstrate small to medium effectiveness in facilitating PEB (Beermann, Rieder, & Uebernickel, 2022; Mertens et al., 2022; Wee, Choong & Low, 2021). However, few IS studies leverage the capabilities of cognitive computing systems (which are adaptive, interactive, iterative, and contextual) (Schuetz & Venkatesh, 2020). An exception is Tiefenbeck et al. (2018), who tap into the potential of cognitive computing systems by installing a display in a shower that provides adaptive real-time feedback on water and energy consumption during showering. The strong effects they find lead to the conclusion that incorporating cognitive qualities into nudges could increase their effectiveness. Sensemaking and formation of sustainable beliefs could be enhanced through such cognitive capabilities, after which pro-environmental beliefs translate into behavioral intention and finally into PEBs (cf. Degirmenci & Recker, 2016).

Unlike laws and other kinds of mandates, nudges are easy to implement and allow freedom of choice (Thaler & Sunstein, 2003). In particular, nudges that prompt reflection about a choice can preserve dignity and agency (Sunstein, 2016). In addition, technology has the potential to scale nudges toward larger audiences (Schneider et al., 2016) and inform decision-makers to favor PEB over less sustainable behaviors (Seidel et al., 2013). However, ways to affect outcomes directly that offer low hurdles for organizations and policymakers are needed. In this process, algorithms would allow us to leverage organizations' and society's ubiquitous data and to personalize and contextualize the resulting information to prompt reflective thinking so individuals can make sound decisions and contribute to the transformation toward sustainability.

3 Hypotheses

We developed our hypotheses based on Seidel et al. (2013), who propose that reflective disclosure and information democratization allow for environmental sensemaking. Empirical evidence shows that both of these dimensions are effective on their own and that applying both yielded no additional benefit (Degirmenci & Recker, 2023). Given this study's research objective of determining the effect of algorithmic nudges on PEB, we focus on reflective disclosure (i.e., monitoring, analysis, and presentation of data). Reflective disclosure facilitated PEB in, for example, reducing paper consumption (Degirmenci & Recker, 2023; Seidel et al., 2013), conserving water (Tiefenbeck et al., 2018, 2019), energy (Loock et al., 2013), and fuel for driving. Artifacts that rely on reflective disclosure provide feedback on a specific measure (e.g., electrical energy consumption) that is closely tied to a PEB (e.g., behaviors that use electricity). With the help of data (e.g., from smart meters), reflective disclosure raises individuals' awareness of their behavioral patterns and increases their potential to adopt more sustainable forms of behavior (i.e., waste less electricity) (Loock et al., 2013).

Building on the sensemaking and nudging literature, we identified three central properties of IS that can facilitate environmental sensemaking: First, **transparency** of personal information can help individuals understand which outcomes (e.g., kWh consumption) will be influenced by their behavior (e.g., using electrical devices and appliances). For example, Tiefenbeck et al. (2019) show that transparent real-time feedback on resource consumption while showering reduced hotel guests' energy use by 11.4 percent.

Second, **references** to the social environment support individuals in classifying and orienting their behavior to norms. For example, Demarque et al. (2015) find that displaying what most people do ("70% of previous participants") had a significant influence on the purchase of products in an online shopping environment. Social references present guiderails for orientation and allow for sensemaking about individual behavior. Third, showing the **consequences** of one's behavior facilitates reflective thinking about future decisions. For example, Abrahamse et al. (2007) show that providing customized feedback about energy savings led to a 5 percent reduction in consumption.

Transparency, reference, and consequences are all part of the sensemaking mechanisms of reflective disclosure (cf. Seidel et al., 2013). Nudge artifacts that use these three properties to prompt reflective thinking and support the decision-maker with information and assistance can be classified as non-manipulative (Hansen & Jespersen, 2013), and we propose that their effects are additive. For our first set of hypotheses, then, we propose the following:

H1.1: Transparency of personal information significantly increases PEB.

H1.2: References that help individuals to classify their behavior significantly increase PEB.

H1.3: Showing the individual consequences of behavior significantly increases PEB.

Reflective disclosure manifests in various forms, ranging from simple feedback systems (Schultz et al., 2016) to more sophisticated data presentations (Haki et al., 2022). Although research investigates several forms of feedback systems, the literature does not provide a definitive answer regarding what makes some features of reflective disclosure more effective than others. We suggest that the more meaningful the information, the more it facilitates the belief formation that influences PEB. Feedback in the form of raw data (e.g., kWh for heat and electricity) provides some level of meaning to individuals, but algorithms can turn raw data into more meaningful information (e.g., social feedback or impact on the environment). To evoke sensemaking and belief formation, algorithms must be designed to reduce ambiguity and to be accurate and accessible (Möhlmann et al., 2023). (We designed our algorithms and features in this way.) Therefore, we hypothesize that the more information that is incorporated into the IS property (instantiated as a feature) and the more meaningful the property is to the individual, the larger the effect is on PEB. For example, in Jain et al.'s (2013) study in which individuals were given kWh and CO_2 emissions as feedback about consumption, information about CO_2 emissions led to a more significant reduction in energy use. We hypothesize that different degrees of "smartness" in nudges result in different outcomes, such that the "smarter" the nudge is, the more effective it is.

We also differentiate between the perspective of the choice architect who designed the IS property and how the users experience it. For example, Anderson et al. (2017) find that information about social norms caused a 14 percent reduction in energy use over two years by people who were significantly concerned about social norms but a 5 percent increase in energy use by people who were not so concerned. Therefore, we hypothesize the following:

H2.1: The more information that is incorporated in the reflective disclosure feature, the greater its impact on PEB.

H2.2: The greater the extent to which individuals make sense of the reflective disclosure feature, the greater its impact on PEB.

As reflective disclosure features address belief formation, the translation toward the pro-environmental intention that increases PEB occurs over time. Some research finds that the effects of feedback nudges are stable over time (Allcott, 2011; Tiefenbeck et al., 2018), but other studies find an increasing impact (Beermann, Rieder, Ebbers, et al., 2022). Complex target behaviors, defined as behaviors that have multiple outcomes and consequences, require interventions that addresses the complexity in adequate terms (Haki et al., 2022). Therefore, the more complex the target behavior is, the more sensemaking is required. We propose that algorithmic nudges have the potential to influence belief formation, and as belief formation is a time-dependent process that leads to behavioral intention and PEB, we expect to see this pattern in our experiment. Therefore, we hypothesize:

H3: Repeated exposure to reflective disclosure increasingly affects PEB.

4 Method

To investigate our hypotheses, we designed three green nudges for a mobile application that we will test in a longitudinal field experiment. The longitudinal field experiment guarantees high external validity (Levitt & List, 2009), so our results can translate to applied settings and have the potential to be of value to organizational leaders and policymakers. The longitudinal design also allows us to evaluate time-dependent effects.

Our experiment is situated in two residential buildings with around 1,500 apartments for international students in Berlin, Germany. Each apartment is equipped with a smart meter that captures daily heating, electrical energy, and water consumption, and our nudge design draws on this data.

4.1 Nudge Design

We followed the digital nudge design method that Mirsch et al. (2018) propose.

Context: The first step is to analyze the context to ensure a fit between the nudge and the user. Cresco Immobilienverwaltungs GmbH (Cresco) is a real estate company that provides living spaces for international students. The tenant population is young, diverse, and international. Two-thirds of the population reside in the apartments for two semesters (~Oct. - ~Sept.) and one-third for one semester (~Oct. - ~Mar.), where about 10 percent of the latter group renew their contracts for another semester. The tenants pay an “all-inclusive rent,” so they are not financially motivated to conserve water or energy. Therefore, the nudge must focus on non-financial motivators like environmental concerns. An initial survey of 205 current Cresco tenants indicated that 89 percent were interested in being informed about their energy and water consumption. We also analyzed the daily data of 1,262 tenants from December 1, 2021, to July 20, 2022, and found a right-skewed distribution in four clusters: low consumers (735 tenants, daily ~5.2 kWh and 0.5 kg CO_2 emissions), mid consumers (432 tenants, daily ~12.1 kWh and 0.8 kg CO_2 emissions), high consumers (94 tenants, daily ~23.1 kWh and ~1.24 kg CO_2 emissions), and extreme consumers (1 tenant, daily ~109.5 kWh).

Ideation and Design: In the second step, we ideated and designed the nudge based on the context (i.e., conserving water and energy), the scholarly literature (i.e., focusing on algorithmic nudging, PEB, and sensemaking), and our technological opportunities (i.e., smart meter data and a mobile application). We designed three nudges: (i) a *consumption* nudge using consumption feedback (e.g., in kWh), (ii) an *eco-score* nudge that compared the sustainability of a tenant to that of all other tenants, and (iii) a *CO_2 emissions* nudge as the consequence in terms of the carbon emissions from what the individual consumes. The eco-score and the CO_2 emissions use algorithms to transform daily consumption data into meaningful information.

To construct the eco-score, we obtained the CO_2 emissions per unit from each utility provider and considered the influence of weather and apartment size. The eco-score describes the relative consumption of each tenant in the sample, so it is classified into six classes, ranging from A (i.e., top 10% of the scores; very sustainable) to F (i.e., the bottom 20% of the scores; very unsustainable). The better categories are more exclusive (i.e., A = 10%, B and C = 15%) than the average and unsustainable categories (i.e., D, E, and F = 20%). Research demonstrates that people with the most potential show the most significant conservation effect (Allcott, 2011). To ensure algorithmic sensemaking (Möhlmann et al., 2023), the design of the A-F rating is transparently communicated in the application.

Table 1 displays our mobile application’s nudging features and operationalizations as design elements. Tenants can also access other features in the mobile application, such as coupons for reduced prices for food or car-sharing providers and a chat feature with which to interact with other tenants, manage their contracts and profiles, or contact Cresco about their apartments. The nudging features are presented dominantly on the home screen and are at the top position in the application’s overview menu. The application's additional features make it more likely that the tenants will use it, increasing the chance that they will interact with our design elements.

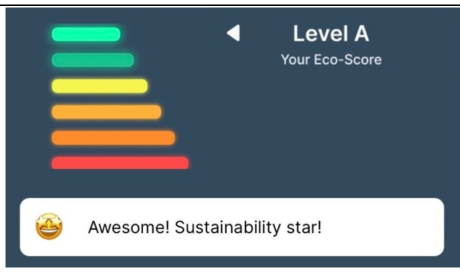
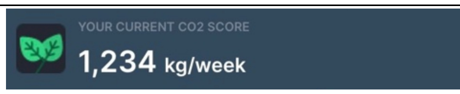
Nudging Feature	Design Element	Description
Consumption (Transparency)		Electricity and heating energy consumption in kWh; water consumption in liters.
Eco-score (Reference)		Eco-score classification from A (= very sustainable) to F (= very unsustainable) based on comparison with peers. Evaluation statement regarding the eco-score class (A = “Sustainability star”).
CO_2 emissions (Consequence)		Translation of consumption into CO_2 emissions.

Table 1. Nudging features of the mobile application.

4.2 Experimental Design

The target behavior is lowered electricity, heat energy, and water consumption. We designed one control and three experimental conditions based on the features from Table 1. Those in the control condition receive no features, although they can use the mobile application to access the other features (e.g., contract management). Those in the first experimental condition receive the consumption feature, which provides transparent feedback on water and energy consumption in raw numbers (i.e., energy use in kWh and water use in liters). Those in the second experimental group receive an eco-score in addition, along with its classification (A–F). Finally, those in the third experimental condition receive all three nudges, including translation of energy and water use into CO_2 emissions. Table 2 summarizes the conditions of our experiment.

We expect that those in the consumption condition (experimental condition 1) will consume less than those in the control condition, that those in the eco-score condition (experimental condition 2) will consume less than those in the consumption condition, and that those in the eco-score plus condition (experimental condition 2) will consume less than those in the eco-score condition.

Reflective Disclosure	Control	Consumption	Eco-score	Eco-score Plus
Transparency	x	√	√	√
Reference	x	x	√	√
Consequence	x	x	x	√

Table 2. Experimental design and nudge characteristics.

We took a baseline measurement of water and energy consumption from move-in in September/October 2022 until the end of November 2022. At the end of the baseline period, we allocated participants into one of the four experimental groups (i.e., Control. Consumption, Eco-score, Eco-score Plus) and stratified them in terms of their aggregated energy and water consumption such that participants in each group had the same consumption profile (cf. Andor et al., 2020). The stratification was determined by an algorithm that defined the daily eco-scores of the tenants based on their consumption during the baseline measurement. We averaged and rescaled the users' scores over all days per category and, finally, took the weighted average to estimate the overall eco-score class (i.e., the six classes A, B, C, D, E, and F). Then we randomly distributed the population of each eco-score class equally into the four experimental groups described in Table 2. The experiment started in the winter of 2022/2023 and lasted 8 weeks. To detect a small effect with 90 percent power, 1,212 participants (around 80% of the tenants) had to participate and consent to the experiment. We evaluated the between-subject design of the four conditions by comparing the weighted aggregation of energy and water consumption, and at the end of January conducted 20 qualitative interviews with participants to investigate the participants' sensemaking process.

5 Expected Contribution and Next Steps

By including backend components of IT in the form of algorithms that monitor, analyze, and present information, we set out to extend the current definition of digital nudges, which focuses on user-interface design elements in the frontend (Weinmann et al., 2016). We argue that backend data that is harnessed to design nudges with cognitive capabilities (cf. Schuetz & Venkatesh, 2020) allows the backend to contribute substantially to the nudge's effectiveness (cf. Mele et al., 2021; Möhlmann, 2021) and this aspect must be considered in the definition of digital nudges. The literature describes personal information presented to individuals as reflective disclosure (Seidel et al., 2013), but the forms in which reflective disclosure—also called feedback—is presented vary from static to dynamic (Buckley, 2020). Since personalized and contextualized nudges are found to be more effective than their static counterparts (Buckley, 2020), we seek to identify the mechanisms that increase effectiveness. By monitoring, analyzing, and presenting personalized and contextualized information, algorithms help individuals in their sensemaking as it relates to embracing PEB (Seidel et al., 2013). With the proposed research, we investigate whether algorithm-infused design elements are more effective than less informative nudges and what gives rise to their effect.

Our research has practical implications. As data becomes increasingly ubiquitous, designers of IS can use it to provide individuals with better information. Thus, nudges can grow smart and evolve in proportion to the data available on behavioral patterns. Our research might be useful to housing providers with smart metering systems, energy and water providers, and policymakers. Our findings can also be adapted to other contexts in which data can be turned into valuable information for individuals.

We address a specific population of international students (i.e., average age 23, culturally diverse, resident of a particular apartment building for 6–12 months), so the generalizability of our research is limited. However, we compared our sample's average consumption to the state average consumption and found a similar pattern for water consumption, so limited generalizability in some regard might be warranted.

Our next steps are to prepare to roll out the mobile application and to carry out the experiment. We expect to present our findings at a conference in June 2023.

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