Empowering User-Centered Carbon Management: Bridging Individual Preferences and Sociotechnical Advancements

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ABSTRACT

There is a widespread agreement that society must swiftly decrease and ultimately eliminate its carbon emissions to mitigate climate change, a profound threat to the Earth's ecosystem and humanity's existence. Over the past decades, previous research has primarily motivated individual consumers to lower their energy consumption, with several works reporting financial incentives as the key reason for participation. Contrary to intuition, the core issue is not the escalation of energy consumption itself, but the carbon footprint resulting from that energy usage and its environmental consequences. As such, recent initiatives aimed at decarbonization in fields such as computing, construction, and transportation leverage the flexibility of energy demand to effectively diminish its associated carbon footprint. In addition, consumer habits and routine changes have been argued to significantly achieve large energy savings. However, most approaches mainly use financial incentives, which alone cannot be employed as the primary strategy with results pointing to individuals reverting habits due to low rewards and considerable impacts into their routines. In a world where automation spans various applications, Artificial Intelligence (AI) can potentially assist consumers in reshaping daily behavior to lower carbon footprint, all while mitigating inconvenient factors associated with routine changes. In this paper, we propose a vision of using the modeling of sustainability efforts with human-in-the-loop considerations. We begin with understanding what incentivizes behavioral change among consumers. Then, we describe, illustrate, and list the challenges in using automation technologies with recommendation systems to sustain consumer engagement in day-to-day decarbonization efforts.

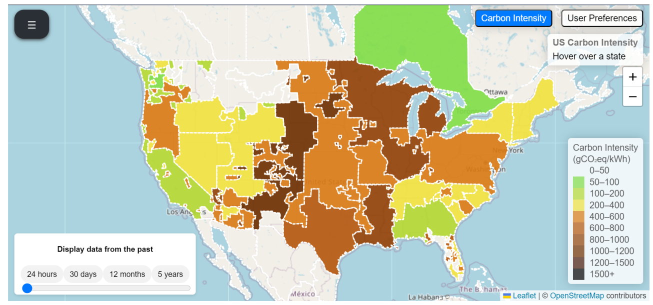

Figure 1: ***North American grid overview for 2022 – Color-coded representation of the average carbon footprint (in g·CO_2Eq per kWh), with greener colors representing cleaner electricity. The low number of green regions indicate heavy reliance on fossil-fuel-based energy generation nationwide.***

1 INTRODUCTION

The growing concern about the climate impact of human activities has highlighted the focus on the Greenhouse gases (GHG) footprint linked to energy consumption across different sectors of society, in which carbon dioxide emissions are the main contributor. Hence, a significant concern pertains to the tangible manifestation of energy generation and its carbon footprint. While adopting new sustainable technologies is promising, the success of reducing carbon emissions will largely depend on *user willingness to adapt their behavior*, requiring changing habits and maintaining them as a routine to align with periods when renewable energy is abundant. The expectation for everyday users to comprehend these consequences, analyze and consequently alter their daily behaviors to collectively reduce society's carbon footprint has emerged as a pivotal solution, both from a political and environmental standpoints.

In the context of climate change and sustainability, the main goal extends beyond merely reducing energy demand — it also encompasses diminishing the carbon footprint associated with everyday activities. Although there have been decades of research dedicated to enhancing the energy efficiency of societal activities in areas such as transportation [27], dwelling acclimatization [28], agriculture, just to name a few, there has been relatively less emphasis on improving *carbon efficiency*. Carbon efficiency describes the effectiveness of an activity, process, system, or technology to minimize or reduce the overall carbon footprint associated with its operationalization. This definition highlights that, contrary to common perception, the primary issue is not the exponential increase in energy demand itself; instead, it is the resulting carbon footprint associated with such demand and its environmental repercussions. The difficulties and overlooks by technology developers and industry players with carbon efficiency are primarily driven by the need to closely integrate and understand frequently opaque energy systems. Nevertheless, optimizing carbon efficiency is imperative for satisfying society's growing energy demands sustainably without relying on unattainable increases in energy efficiency.

While studies have reported various factors impacting carbon efficiency and vary depending on the specific area of study [1], the implications of these findings underlined growing societal awareness of the existing impact of climate change and its severe consequences. Much research has argued that the effects of individual behavioral changes hold significant promise in improving climate change. Strategies to encourage everyday consumers to change their behavior, however, too often relied on extrinsic motivation such as financial rewards, lowering electricity bills, discounts, and penalties. Despite attractive monetary incentives, these strategies are less effective as long-term solutions due to users' habits and preferences [30]. More often than not, the behavioral change expected from the user raises impractical inconveniences, consequently resulting in users reverting to their energy-inefficient practices. Social science research has argued that behavioral change strategies must appeal to intrinsic motivation to sustain long-term actions. They must be driven by one's autonomy, leading to personal satisfaction. Some works have reported that strategies appealing to personal health and comfort needs play critical roles in nudging and retaining pro-environmental behavior [8, 12].

In addressing these issues, research in smart homes and the Internet of Things (IoT) has introduced home appliances with the ability to autonomously regulate energy consumption while allowing users to monitor their energy consumption, automate the operation of specific devices during periods of lower electricity costs, and deactivate unused appliances [2]. While effective in serving their purposes, these efforts have primarily focused on energy utility and less on carbon savings. Further, the ability to monitor energy usage can be expanded as a promising modality to raise awareness of the impacts of changing everyday behavior on carbon emission through a broader spectrum of daily actions. For example, it can range from prompting users to dim their home lights to lowering their streaming resolution to reduce their digital carbon footprint.

Our vision is to address decarbonization with human-in-the-loop consideration. We argue that changes in user behavior with respect to reducing their carbon footprint can be properly mitigated through informative, automated systems without imposing high burdens on the user. Accordingly, this paper proposes a user-centered decarbonization management framework that pairs energy system optimization models with an AI-augmented user behavioral intervention mechanism. By collectively and intelligently optimizing for the user, our work aims to reduce burdens associated with participation, and to proactively engage in pro-environmental behavior yet assist users with making carbon-efficiency choices while accounting for their habits and preferences. The third component of raising decarbonization awareness is through an interactive visualization that can aptly identify the challenges and opportunities in formulating carbon-efficient policies targeting various settings and user groups.

Our vision for a user-centered carbon management system proposed in this paper aims to contribute to the ongoing discussions about policies and mechanisms that align macro-user behaviors and their preferences according to the availability of lower carbon periods.

2 BACKGROUND

The groundwork for this research hinges on advancing the grid carbon intensity model and methods of incentivizing users to change their behavior. In this section, we provide an overview of the electric grid's carbon intensity, different types of carbon intensity signals and how these are used to do accounting, and used in carbon-aware several applications.

2.1 Energy Information Services

The electric grid combines energy sources to fulfill the local electricity demand. These sources encompass fossil fuel-based generators, coal or natural gas, renewable sources such as hydro, wind, and solar, as well as non-carbon sources like nuclear power. Due to fluctuations in electricity demand over the day, following the diurnal cycle, the composition of generation sources and their relative contributions vary over time. It is important to note that renewable sources such as wind and solar are intermittent, adding a temporal layer of complexity to the generation mix. The carbon intensity (CI) of the electricity supply, quantified in grams of CO_2 equivalent per watt or g·CO_2eq/kWh, denotes the average weighted carbon emissions associated with the mix of generation sources in use at any given moment. This average intensity is influenced by the proportion of each source in the generation mix, with fossil-based sources factoring high footprint weights and renewable sources factoring low or near-zero carbon impacts.

The recent emergence of carbon information services [22, 29] has marked a significant development in environmental awareness and sustainability. These services offer insights by providing real-time data on the carbon intensity of electricity generation, empowering individuals and organizations to make informed choices about when to consume energy and enabling them to control their carbon footprint. It also contributes to a broader global effort to transition toward cleaner and more sustainable energy sources, highlighting the growing importance of technology and user-driven solutions in addressing environmental challenges. For instance, Figure 1 depicts our web-based visualization tool with the overall carbon intensity of grid electricity throughout 2022 across various geographic regions in North America [21]. Notably, the map highlights substantial spatiotemporal disparities, with the carbon intensity exhibiting significant differences across regions and an even greater contrast to Ontario, which has a large renewable penetration, over the same period. In North America alone, these disparities illustrate significant variations in the carbon footprint of energy-intensive activities. They can be further broken down by periods of high or low carbon intensity. More importantly, the low number of green regions indicates a heavy reliance on fossil-fuel-based energy generation nationwide.

2.2 Mitigating Carbon Emissions

The task of designing energy-efficient activities is intuitively straightforward, involving the optimization of individual components to minimize their energy consumption. Additionally, they can be achieved simply by using less energy-intensive alternatives. In contrast to energy-efficiency solutions that specifically aim to reduce energy usage, designing carbon-efficient solutions is more intricate, necessitating a broader perspective about how and when to use and create energy demand. It requires considering the local energy system and grid, the energy source, and the characteristics of the energy used, which largely depend on temporal and geographical aspects, and the kinds of user activities.

Most modern products and services are linked to energy generation. Even when considering sectors such as transportation, agriculture, and construction, a significant portion of their CO_2 emissions results from the combustion of fuels. From an environmental standpoint, electrification projects can only realize their full potential when the energy fueling these initiatives is environmentally friendly. For instance, the success of Electric Vehicles (EVs) surpassing that of internal-combustion engine vehicles becomes less relevant if, ultimately, these EVs are charged with energy derived from fossil-fuel-based power plants. Similarly, this reasoning can be extended to apply to all electrification and digitalization projects that have been recently announced, whereas major industries have committed to reducing their carbon emissions, primarily by improving energy efficiency and by offsetting their footprint through power purchase agreements. Nevertheless, these offsets are considered independent of location when factoring in carbon emissions, significantly constraining their actual advantages.

2.3 Incentivizing Behavioral Change

Demand Response: Various research underscore the potential for modifying household consumption behavior through improved accessibility of energy reports. By and large, demand-response programs promote behavioral change through price-based energy usage, where consumers pay different prices at varying peak loads or receive some financial discounts to retrofit their homes with recommended green energy practices. A comparison of monetary payments, energy information, and daily feedback in student housing complexes revealed that monetary incentives resulted in immediate and substantial reductions in consumption across all units, even when the payment amounts is significantly reduced [14]. While the success of these programs was theorized to reduce peak demand by up to 180 megawatts (i.e., equivalent to 85.8 tons of CO_2Eq), energy saving from local programs only led to 0.1% of all conservation efforts [24]. Moreover, multiple research studies have concluded that these systems exert a more pronounced influence on energy awareness than on actual conservation behaviors, irrespective of whether they are implemented in high-income or low-income households [2, 4]. When aiming for enhanced carbon-efficient performance, AI and autonomous decision making systems have the potential to improve user consciousness in relation to their energy consumption. Today, feedback has evolved beyond simple indicators to encompass smart Internet-of-Things (IoT) devices and gamification techniques. The limitations from these approaches lie on the often requirements of active user participation and engagement [6]. By integrating real-time data from IoT devices with AI-driven recommendations and autonomous decision making systems, users can receive tailored insights and actionable suggestions, empowering them to reduce their carbon footprint while maintaining convenience and comfort in their daily routines [6].

Consumer Behavior, A Challenge: A substantial body of work offering psychological and social perspectives emphasized that monetary benefits alone are insufficient for behavioral change [9]. Where the intention is to *motivate consumers to act*, financial incentive is a common reason for initial participation. However, retaining this behavioral change in real-world practices is significantly influenced by personal *habits* and *routines* [9, 31, 32]. Much research has argued the lack of generality in retaining this behavior is consistent with the Theory of Planned Behavior [3, 9, 11, 25], whereby an intention is influenced by one's attitude, subjective norm, and perceived behavioral control. Further, moral obligation describing the sense of responsibility for climate change is suggested to strengthen such intentions [10, 13]. Other works have also reported that personal health and comfort needs factors play critical roles in nudging and retaining pro-environmental behavior [8, 12]. Additionally, several new IoT based devices with AI capabilities have been offered to the consumer based markets. As an example, Apple has introduced a 'Grid Forecast' section within the Home app for their iOS17 [20]. This feature leverages users' location to inform them about periods when clean energy is readily accessible, enabling them to make more conscious decisions about their energy usage. However, users are still required to proactively review forecasts, and there are no interfaces in place to facilitate automated decision-making.

Digital Behavioral Change: As the digitization of society moves at an increasing pace, in this decade, we will see cloud datacenters handling yottabyte (~1 trillion-terabytes) amounts of data. From smart sensors used in households to large turbines in remote areas, millions of devices are now connected to data centers through IoT. Moreover, the recent advancements in AI, particularly within the realm of deep learning, have ushered in a new era of applications, including for IoT-connected devices such as smart appliances. These various aspects of digitization have created an extraordinary opportunity to tackle the ongoing limitations of smart household and building appliances. By learning about the users who use these digitizations in their daily lives, coupled with the expanding adoption of information technologies, electricity pricing dynamics, and various other demand-driven factors, AI can be used to assist with behavioral change that takes a user-centric stand in reaching societal sustainability goals.

2.4 Summary and Research Gap

As the consensus on climate change and growing worldwide efforts to reduce carbon emissions solidify, residential buildings are increasingly adopting energy-efficient measures. Advancing technologies of smart meters, controllers, and appliances promise to deliver energy efficiency while providing more comfortable, convenient, and healthier living environments. Paradoxically, in some instances, these measurements may undermine their very energy reduction goals [2, 23]. As such, the overall associated GHG emissions in U.S. households have not seen a decline [19], while Canada reportedly needs to accelerate carbon reduction to reach its future goals [15, 26]. The demand for solutions must now extend beyond mere introduction and immediate impact: it necessitates establishing sustained, global-scale approaches. One crucial challenge lies in not only developing models that can adapt to individual user preferences but also in imbuing these models with the intelligence to effectively promote meaningful behavioral change, while minimizing user burden. In this paper, we propose that despite the possibility of these technologies inadvertently raising energy consumption [2], they can also serve as tools for establishing user-centric carbon-aware mechanisms that can empower individuals to actively manage their carbon footprint while mitigating the adverse effects that might otherwise restrict their effectiveness.

3 TOWARD AI-ASSISTED DECARBONIZATION

This section outlines the framework encompassing our vision, along with the key components required for the effectiveness of its user-centric, carbon-awareness approach.

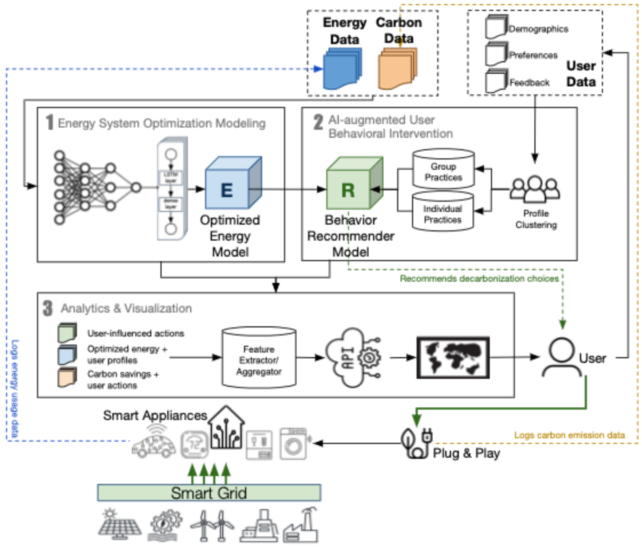

Figure 2: ***A three part module driving a user-centered decarbonization management system – We extend the rich body of work established in (1) to develop an AI-augmented user behavioral intervention mechanism (2). Energy, carbon, and user data and predictions serve as input for our visualization, purposed to raise decarbonization awareness (3).***

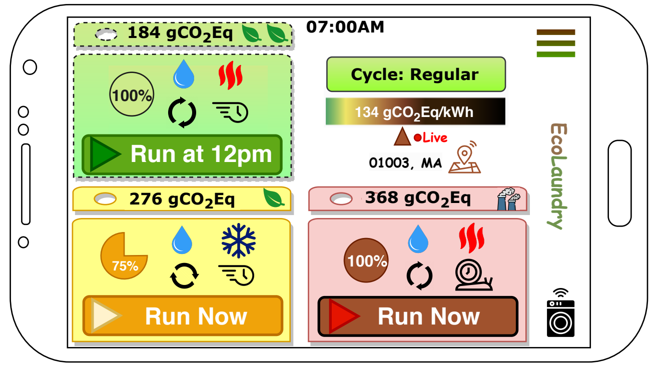

Figure 3: ***The EcoLaundry app provides users with recommendations for scheduling their laundry loads based on carbon footprint (in g·CO_2Eq). Users can choose to run their load during low-carbon periods (green), opt for a low-intensity setting with cold water that reduces energy consumption (yellow), or freely select the highest-intensity profile without energy-saving constraints (red).***

3.1 User-Centered Management System

Figure 2 depicts a three-part component to establish a user-centric cyber-physical system (CPS) and decarbonization management environment. We discuss a set of key design modules that can aid in bridging system optimization modeling with human factors to enable intelligent behavioral change for consumers as follows:

Energy System Optimization Modeling: There is a widespread research in the substantial energy-saving potential of household and buildings through modeling [17]. Energy systems engineering offers a systematic and scientific methodology for modeling pragmatic, integrated solutions to intricate energy challenges [5, 7]. Consequently, the initial module (1) illustrated in Figure 1 represents the component responsible for modeling the energy profiles of smart appliances and the data from the smart grid. Utilizing various approaches, this module employs data engineering to combine this information, resulting in a range of optimal and near-optimal energy profile settings that household appliances can set. Additionally, it possesses the capability to generate What-If scenarios [16], which are subsequently integrated into the AI-augmented User Behavioral Intervention (2).

AI-augmented User Behavioral Intervention: This module combines two key optimized settings output by the Optimization Module (1), with the user profile and the data pertaining their preferences. This module can be supplied with data gathered from different representative surveys [18] and scatered from public reports. Post-processing can derive typical user energy consumption behaviors and serve as a resource for estimating users' willingness to reduce their footprint, besides suggesting incentives to encourage eco-friendly habits. Furthermore, it enables stakeholders in Cyber-Physical Systems to conduct quantitative analyses, examining factors that influence and to what extent users are engaged in reducing their footprint. Additionally, the application of clustering algorithms can unveil distinct profile patterns. For instance, certain user groups characterized by specific socioeconomic and demographic profiles can exhibit a greater propensity for adopting carbon-friendly practices.

Analytics and Visualization: This third component provides users and stakeholders with a clear and concise overview of the effects of their carbon footprint, segmented by user profile (e.g., age, demographics) and energy usage temporal patterns. It also aggregates user-provided feedback in order to dynamically adapt and create specialized recommendations as to how suggestions are provided. By integrating various data sources accumulated through the previous modules, the dashboard can provide actionable insights to support raising societal awareness and behavioral change, all while mitigating user inconvenience. Data sources include aggregates of users' behavioral preferences and routines, and energy usage for daily activities, enabling the visualization of carbon data, demographics, and energy consumption habits by region and states and by activities. Figure 5 presents our first version of this visualization dashboard through our web tool. To elevate our geospatial data representation, we integrated the Leaflet JavaScript library into our framework.

3.2 Design Objectives

Our user-centric system must simultaneously satisfy the goals of digital systems, while reducing carbon emissions (as a result of) and promoting long-term behavior change. Fulfilling these objectives necessitates primarily three characteristics[1]:

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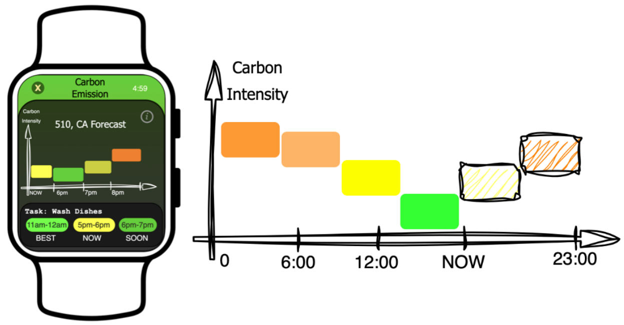

Figure 4: *The EcoWatch app assists users in scheduling dishwashing, with carbon intensity forecasts (left), and historical data visualization (right) to enhance user awareness about daily temporal patterns.*

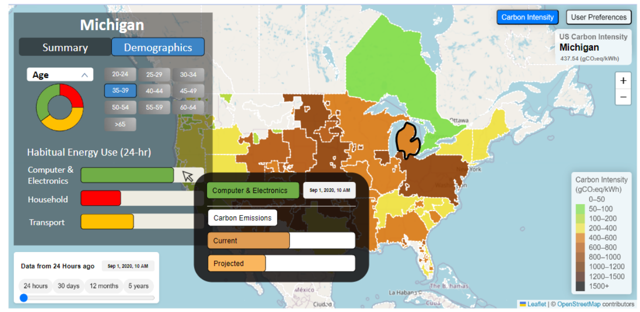

Figure 5: *Access to carbon intensity information by user profiles and device usage via our visualization dashboard. This visualization tool serves as a valuable resource for policymakers and researchers, enabling them to visualize trends in footprint by population demographics and geographic regions.*

Encourage meaningful user actions: Instilling meaningful behaviors among consumers will require educating everyday users on the subject and simplifying carbon footprint assessment. Our work requires integrating interfaces that can prompt users of projected carbon savings and the extent to which their choices can save the environment. Figure 3 illustrates how choices on device usage based on carbon-efficiency measures can be simplified to better guide users in making their decisions. In the case of utilizing a laundry machine, the selection of water temperature and time of use translate to how much carbon a user can potentially save.

Assist in Scheduling Based on Carbon Footprint: Figure 4 illustrates the EcoWatch, an application similar to how weather forecasts influence daily plans but where users can visualize carbon intensity forecasts. This app enable users to benefit from scheduling activities based on carbon intensity through forecast integration to automate smart appliances. By understanding the amount of energy needed to execute or participate in an activity e.g., light dish washing cycles, users can easily take informed decisions when planning their tasks accordingly to low carbon periods, making it convenient and engaging. In situations where users have already initiated energy-intensive activities during high-carbon periods, recommendation systems that can suggest lower-energy alternatives can be helpful. The goal is to provide readily available, less carbon-intensive options, even if they require slight adjustments. While current solutions such as the Apple Watch only leverage forecasts [20], incorporating historical data visualization could enhance user awareness temporal patterns.

Globally-accessible consolidated carbon data: It is essential to offer users systematic and meaningful feedback on their behavior changes and impacts to evoke intrinsic motivation and reinforce carbon awareness. Unfortunately, however, one's carbon savings is not bounded by borders. Figure 5 shows our visualization dashboard aims to consolidate the results of carbon emissions from digital device usage, with options to segment carbon savings by demographic and socioeconomic makeup. The ability to access carbon data at this scale can define clear standards of conduct for digital device use, facilitate community outreach in less engaging groups, and drive for policy change. We emphasize the significance of integrating analytical forecasts for socio-technical advancements in order to understand R&D for energy-related decision-making processes. Our vision incorporates various modules to enhance comprehension and facilitate the development of refined protocols, ultimately resulting in more accurate and adaptive recommendations regarding the footprint outcomes in household and building automation.

4 IMPLICATIONS AND CHALLENGES

The critical drivers, beyond reducing energy are sustainability and reducing carbon footprints. Despite decades of continuous efforts (primarily in reducing energy), reports of short-term changes in user behavior present a significant challenge. Reinforcing conclusions from prior studies, the extrinsic motivation of offering monetary incentives, such as electricity bill savings, has proven insufficient. They yielded short-term results, permitting users to revert to previous habits over time. To nurture decarbonization efforts, the strategy to motivate change among consumers must take on a different front – *What constitutes meaning and long-term behavioral change among everyday users?* The prevalence of intelligent modeling techniques and IoT devices can converge to support context-aware decarbonization strategies in *virtually* all digital systems today and assist users in making pro-environment decisions and maintaining such habits. The key to our research is evaluating whether AI-augmented recommendations can, in fact, foster long-term behavior changes without the prior setbacks observed in other work. The challenge lies in minimizing user inconveniences while ensuring participation is passively but intrinsically motivated (i.e., without requiring active user actions). Herein lies two main challenges:

Information perception translating carbon emissions to GHG reduction: Motivating users to act will require module #2 to explain and help users grasp the true effects of changing their behavior on GHG. As exemplified in Figure 3, our work requires experimenting with UI designs that effectively convey key carbon saving metrics for the decision a user makes.

Standardization of digital applications to provide flexibility in user control: Our system presumes that digital applications will shortly present users with greener options to alter their behaviors on device usage. An example is Apple, which recently rolled out 'Grid Forecast' features to inform users of their availability to 'clean' energy [20]. Everyday home appliances that contribute high energy usage can similarly provide users with timed options during low carbon intensity periods.

Aside from advancing carbon and energy reporting mechanisms and software tools to effectively reduce greenhouse gas (GHG), research in this field must scrutinize the belief that digital solutions and technological management can make up practical strategies to influence users' willingness to act on climate change. To this end, our proposal to nudge users as active participants of decarbonization will delve into these tangible sociotechnical aspects.

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