EcoTailor: Daily Planning System for Negotiating Actionable Low-Carbon Schedules

JEONGWON CHOI, POSTECH, South Korea
DONGHYEON KANG, POSTECH, South Korea
INSEOK HWANG*, POSTECH, South Korea

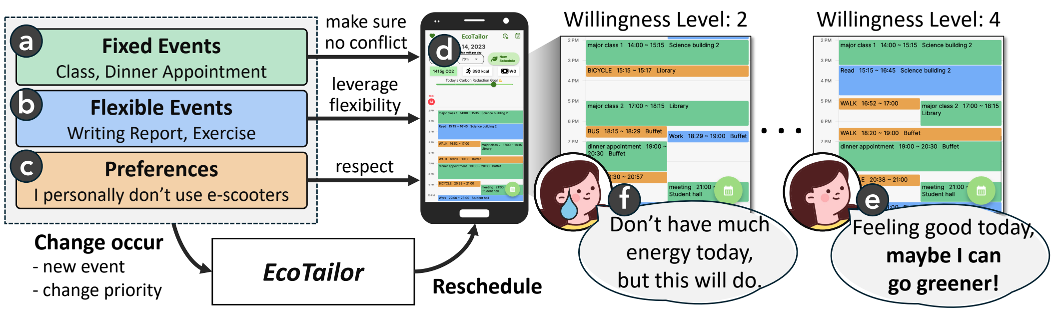

Fig. 1. EcoTailor is a mobile application that provides multiple feasible daily schedule options centered on carbon emissions. Users first input their daily tasks, consisting of a fixed events (with predetermined time or place) and b flexible events (with adjustable conditions), along with c personal preferences. Using this information along with external carbon-emission data and map APIs, EcoTailor generates feasible schedule options (d) and presents them in a calendar view, showing estimated carbon emissions, cost, and physical effort. Users then select the option that best fits their daily conditions (e – f).

Growing concerns about climate change have motivated many individuals to live more sustainably, yet real-life constraints often prevent them from turning awareness into action. Prior eco-feedback systems have effectively increased awareness and motivation but offer limited support for acting within these everyday constraints. To bridge this gap, we present EcoTailor, a personalized daily planning system for negotiating actionable low-carbon schedules around place and transportation choices. EcoTailor helps users organize their daily plans by considering both fixed and flexible events, transportation options, and personal preferences. EcoTailor generates multiple schedule options, allowing users to choose the one that fits their day. Through a multi-phase design, we developed EcoTailor with a mobile application and server. Our scenario-based in-lab study with 38 participants and four-week in-the-wild study with 18 participants revealed that EcoTailor helped users incorporate low-carbon choices into their daily planning. We discuss design implications for helping low-carbon choices fit into everyday routines.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**; **Ubiquitous and mobile computing systems and tools**; *Empirical studies in ubiquitous and mobile computing*.

Additional Key Words and Phrases: actionable scheduling; carbon aware scheduling; negotiation; sustainable HCI

*Corresponding author.

Authors' Contact Information: Jeongwon Choi, POSTECH, Pohang, Gyeongbuk, South Korea, e-mail: choijw@postech.ac.kr; Donghyeon Kang, POSTECH, Pohang, Gyeongbuk, South Korea, e-mail: donghyeon.kang@postech.ac.kr; Inseok Hwang (corresponding author), POSTECH, Pohang, Gyeongbuk, South Korea, e-mail: i.hwang@postech.ac.kr.

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1 INTRODUCTION

As concerns about climate change grow, individuals are increasingly motivated to live more sustainably [7]. While any individual's impact may seem negligible, individuals collectively adopting low-carbon practices in energy use, transportation, and consumption have been estimated to reduce global emissions by up to 31.7% [38]. However, translating awareness into real-life action remains challenging: 65% of adults express concern about climate change, yet only about 30% consistently act to reduce their carbon footprint [64]. To address this awareness-action gap, Sustainable HCI (SHCI) research has made substantial contributions toward encouraging sustainable everyday practices through eco-feedback technology [14, 31]. These systems employ various strategies: visualizing the carbon impact of actions [30, 100], suggesting carbon-friendly alternatives for everyday activities such as driving [9] or shopping [88], and enhancing carbon awareness through gamification [53] or interactive technologies [11].

While these technologies have supported reflection and awareness, they rarely address the real-life constraints that limit individuals' room for sustainable action. Everyday decisions are deeply embedded in personal schedules, social commitments, and contextual constraints such as cost, convenience, or infrastructure availability [75], as the following example illustrates.

> Consider Maya, a sustainability-conscious professional planning her day around a morning online seminar, a dentist appointment, and a new pho restaurant she wants to try. Because several of these are flexible in time or place, her choices interlock—for instance, attending the seminar at a cafe near the dentist reshapes her transit, meal timing, and walking options for the rest of the day.

This scenario illustrates how daily activities are closely interconnected. To support the coexistence of eco-friendly behaviors and everyday life, we focus on two considerations. First, *sustainable interventions benefit from respecting the non-negotiable elements of one's daily routine.* Structural and contextual conditions—infrastructure, institutions, and social arrangements—have been shown to constrain behavior regardless of individual attitudes [37, 91]. Second, *such systems are more likely to be adopted when they align with individuals' priorities and preferences.* Actionability depends not only on tangible resources such as time or cost, but also on one's willingness and priorities [42, 57]. Maya's case illustrates both principles. If her seminar finishes late, it would be impractical to recommend eco-friendly but slower public transport over a taxi to the dentist. In contrast, leaving home early to attend the seminar at a cafe near the dentist makes public transport a viable option; though she pays for a coffee, she saves money and carbon otherwise spent on taxi and home energy use.

Building on this insight, we explore an approach with two aspects: (1) tailoring low-carbon suggestions acceptable within the user's real-life constraints, and (2) adjusting the day's schedule to make low-carbon options more practical. As an initial step, this paper focuses on daily decisions about *when, where, and how* to carry out activities. One's typical day includes some fixed events that occur at specific times and places, and other activities that can flexibly fit around them. People often negotiate how to allocate their time and movement throughout the day, which is being increasingly supported by digital tools such as calendars and task management applications [65, 76]. Leveraging these existing practices, we explore how everyday negotiations—particularly those involving places and mobility—can incorporate *carbon reduction* as an additional consideration.

In this light, we introduce EcoTailor, a mobile application for personalized daily planning that facilitates low-carbon choices in everyday scheduling. EcoTailor considers a user's existing plans, including fixed events and flexible events, together with personal preferences. Based on this information, EcoTailor organizes flexible events around fixed events to produce a feasible daily schedule that suggests different arrangements of places and transportation throughout the day. Users can explore these schedule options and choose a plan for their day, balancing estimated carbon emissions, costs, and physical effort.

Figure 1 illustrates how EcoTailor works. Users first specify their daily tasks according to the flexibility of time and place a–b, along with personal preferences such as transportation modes and acceptable walking time c. Using this information combined with carbon emission data and map APIs, EcoTailor generates feasible schedule options presented in a calendar view d—each showing estimated carbon emissions, cost, and physical effort—so users can select the most practical option for their day e–f.

Throughout this study, we aim to address the following research questions. **RQ1.** How do people interact with tailored carbon-reduction schedules, and what factors make the suggestions easier or harder to follow? **RQ2.** How do carbon emissions change when tailored schedules are provided? To address these questions, we conducted a three-phase study. We first carried out a preliminary study—an online survey (N = 147) and individual interviews (N = 18)—to inform the design of EcoTailor. We then implemented EcoTailor and conducted a scenario-based in-lab study (N = 38) that compared perceived usability and resulting carbon emissions between EcoTailor and an Awareness-raising Condition. Finally, a four-week in-the-wild deployment (N = 18) observed how participants used the system, how they responded to its suggestions, and what differences in daily carbon emissions emerged.

Our results show that EcoTailor could support people in constructing more carbon-friendly daily plans. In the scenario-based in-lab study, participants found EcoTailor usable and easy to engage with, and they constructed more carbon-friendly days with EcoTailor than with the Awareness-raising baseline. In the four-week in-the-wild deployment, participants used EcoTailor's key features to build tailored schedules that fit their varying daily conditions, and interviews revealed the practical considerations that shaped their choices. They also tended to have lower daily carbon emissions when using EcoTailor compared to their typical routines.

Our key contributions are as follows:

- Our preliminary study surfaces considerations for designing carbon-conscious scheduling systems that work within people's everyday constraints.
- We design and implement EcoTailor, a mobile application that generates feasible, low-carbon daily schedules while ensuring that users can still accomplish all their planned activities. EcoTailor enables users to explore multiple options to negotiate a plan that best fits their day.
- We evaluate EcoTailor through a scenario-based in-lab study and a four-week in-the-wild deployment. Across these studies, we obtain both quantitative and qualitative insights into how EcoTailor supports carbon-conscious daily planning.

In the meantime, the following are *beyond our scope*. We do not aim to precisely measure daily carbon emissions. This aspect can naturally improve as more carbon-related data sources and estimation models become available. We also do not directly target increasing people's carbon awareness, which has been widely studied in prior work. Instead, we focus on increasing the practical feasibility of carbon-aware actions.

This paper is organized as follows. Section 2 reviews related work. Section 3 presents study overview. Section 4 outlines the system design derived from the preliminary study. Section 5 depicts the architecture and implementation of EcoTailor. Section 6 describes the design and results of a scenario-based in-lab study, and Section 7 reports the setup and findings of the deployment. Finally, Section 8 discusses limitations and future work.

2 RELATED WORK

2.1 Sustainable HCI

Sustainable HCI (SHCI) has been a topic of interest since the mid-2000s [14, 69]. Early SHCI research focused on shifting individual behavior through feedback, nudging, and goal-setting [28, 29]. Over time, two broad orientations emerged: an *incremental change* perspective focused on individuals, and a *systemic change* perspective emphasizing structural transformation [17, 25, 39]. The *incremental change* perspective supports sustainable individual choices through reflection, awareness, and decision-making. UbiGreen [30] used a mobile ambient display to visualize users' transportation behavior and showed participants' engagement with such feedback. Later work highlighted that uniform feedback is often ineffective: He et al. [42] argued that energy feedback systems had largely adopted a "one-size-fits-all" design, providing identical feedback to users at very different stages of readiness, and proposed tailoring feedback to a user's motivational stage. Overall, eco-feedback and persuasive design can shift attention toward environmental impacts of everyday actions [31], but increased awareness does not consistently translate into practice, as sustainable actions often conflict with everyday constraints [19, 41, 84].

The *systemic change* perspective complements the incremental change perspective by drawing attention to the institutions, infrastructures, and economy within which individual choices are made. Dourish [26] observed that HCI work has tended to recast environmental questions as matters of personal moral choice, leaving political and structural dimensions less visible. Knowles et al. [56] highlight a shift in SHCI toward designing technologies that support people, as citizens or communities, in engaging with the broader systems shaping their daily lives. Together, these perspectives highlight that individual choices are always embedded in larger systems—from transport networks and energy grids to market incentives—that shape what choices are practical or even possible.

While recent work emphasizes systemic approaches, individual-level interventions remain valuable: they can raise awareness [36, 88], foster social consciousness [11], and contribute to collective movements [42]. What remains less explored is how these intentions get enacted in daily life. Sustainable choices often become difficult not from lack of intention, but because they do not fit within these everyday demands [41]. Building on this, we investigate the actionability of individual practices—how low-carbon intentions can be realistically enacted within the constraints of daily life. At the same time, we recognize the importance of collective and societal factors that shape individual actions. In Section 8.2, we further discuss how this approach could extend toward collective and organizational contexts.

2.2 Eco-Feedback Technologies

Eco-feedback technology aims to bridge the 'environmental literacy gap' with contextualized information on how daily activities impact the environment [31]. They take diverse forms—from ambient displays and mobile applications to recommender systems and social platforms—across domains of energy, transport, food, etc. [31, 87].

A foundational approach is providing users with information about their environmental effect [44, 82, 83]. Habits [13], a gamified carbon footprint calculator, presented users with their footprint information, but engagement rarely persisted beyond initial trials, partly due to limited social context and insufficient personalization. Going beyond static feedback, some systems deliver this information through social and emotional channels [24, 35, 68]. INFINEED [10] sought to enhance pro-environmental motivation through a care-based design: a Tamagotchi-inspired avatar with a GenAI-powered chatbot, where the avatar's vitality grew as users adopted energy-saving behaviors. A controlled experiment found this design increased emotional attachment and self-reported energy-saving behavior, especially for less environmentally aware participants. The form of the information itself has also drawn attention. A comparative study of carbon representations found that simple weight-based formats (e.g., kilograms of CO_2) led to greener transportation choices more reliably than elaborate equivalencies [74]. Yet translating this awareness into concrete action is often left to the user.

To bridge this gap, a more direct line of work has guided users on what, when, and how to act sustainably [79]. Envirofy [88] embeds carbon information into online grocery shopping to surface lower-carbon alternatives, breaking down each product's footprint by its sources and showing the cumulative impact of purchasing. Similarly, redesigning washing-machine selection screens to highlight energy-saving options significantly increased users' choice of those programs [36]. Beyond such design proposals, a field study with corporate car drivers found that a smartphone application providing real-time eco-driving feedback reduced fuel consumption by 3% on average [93]. SolarClub [78] visualized forecasts of shared solar generation among neighboring households and let them indicate when they planned to run high-consumption appliances, enabling coordination and demand shifting to greener time slots. However, such suggestions are typically delivered at the moment of a single decision, where broader daily trade-offs—across time, cost, and effort—remain invisible. As a result, low-carbon options that appear feasible in isolation can become impractical when combined into a daily schedule. In response, our work explores sustainability not as an isolated, idealized action, but as a flexible, live practice embedded within existing schedules and places.

2.3 Planning as a Bridge from Intention to Action

Good intentions alone are often insufficient to produce action. Even with strong intentions, people struggle to translate them into action [89], in part due to the absence of a concrete plan for when, where, and how to act [32]. Research suggests that forming such specific plans can increase the likelihood of following through [20, 33]. This insight has motivated HCI work to support translating intention into action through structured planning.

Across domains, planning-based systems show how helping users construct concrete, context-aware plans can support action beyond what feedback or reminders provide. SleepGuru [59] generated personalized sleep schedules that adapt to users' irregular commitments, showing that plans are more likely to be followed when they respect real-life constraints; participants described tailored schedules as "doable," whereas generic guidelines felt impractical. Tateyama et al. [92] found that week-ahead mental health forecasts helped users proactively reorganize their schedules in ways that short-term forecasts did not, and were valued not only for behavioral planning but also for the reassurance of reducing uncertainty about the future. Paruth et al. [80] showed that successful activity plans are associated with identifying "sweet spots"—favorable convergences of time, location, and context—where conditions for action align. Their interviews showed that finding such sweet spots is difficult on one's own, motivating the need for system support. Space-Time Planner [12] further demonstrated that integrating spatial and temporal constraints into a unified interface supports flexible, feasible planning, while allowing users to retain control over plans. Drawing on these findings, we adopt scheduling as a strategy to support actionability in the carbon domain. Prior work suggests such support can make plans feel doable, provide predictability, and integrate with existing routines. We envision that bringing these properties together can open up a way to support low-carbon actions within real-life constraints while accommodating individual differences.

Despite these benefits, sustained engagement with planning-based systems remains an open challenge, shaped by psychological factors such as autonomy, competence, and the gradual internalization of target behaviors [58, 81]. While we recognize the importance of sustained engagement, as an initial investigation, this work examines how EcoTailor can support low-carbon choices through tailored scheduling in daily life. We discuss the limitations of this scope and directions for future work in Section 8.2.

3 STUDY OVERVIEW

In this section, we introduce the motivation and design concept (Section 3.1) and the study procedure (Section 3.2).

3.1 Motivation and Design Concept

Many people are willing to act in environmentally friendly ways, yet real-life constraints often make those actions difficult to follow. Everyday decisions carry environmental implications that often go unnoticed. Maya's scenario in the Introduction illustrates how small scheduling adjustments can open up more sustainable alternatives.

We aim to achieve two complementary goals: (1) to help users find alternatives that are feasible under their current circumstances, rather than ideal but impractical options; and (2) to suggest small rearrangements in daily routines that may create room for sustainable actions. Our system therefore seeks to respect users' real-world

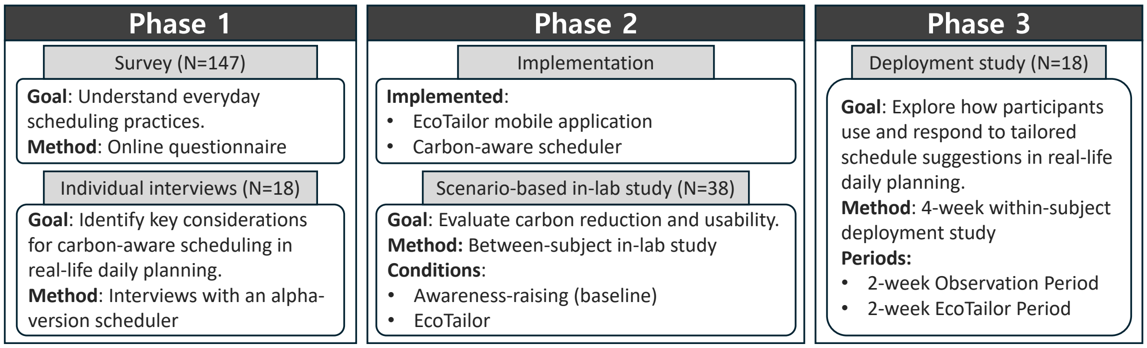


Fig. 2. Overview of our three-phase study procedure.

constraints while reorganizing their day to suggest multiple actionable options. This allows users to preview their day and consider sustainable alternatives in advance, rather than deciding in the moment.

Accordingly, our approach is designed for people whose daily routines include flexible elements alongside fixed ones—for instance, deciding where to work during remote hours, when to fit in errands, or where to spend break time. In contrast, those whose days are almost entirely fixed—such as those with intensive caregiving responsibilities or rigid shift work—may find fewer opportunities for such adjustments.

3.2 Overall Study Procedure

We conducted a three-phase study as shown in Figure 2. **(1) Preliminary Study.** We first needed to understand how people structure daily routines and what trade-offs they consider when incorporating carbon reduction into everyday decisions. To this end, we conducted an online survey and interviews, yielding takeaways that informed the system design. **(2) Implementation and Scenario-based In-lab Study.** Building on these takeaways, we developed EcoTailor as a mobile application. To examine whether tailored scheduling could support eco-friendly daily plans, we conducted a scenario-based in-lab study comparing our system with an awareness-raising baseline. **(3) Deployment Study.** To see how the system fits into real life, we deployed EcoTailor in-the-wild for two weeks after two weeks of observation. We observed how participants used the system in daily planning and what differences in carbon emissions emerged. All studies were approved by our university IRB.

4 PRELIMINARY STUDY

We conducted a preliminary study to identify the key elements that ensure the actionability of system-generated schedules, focusing on how people make everyday scheduling decisions and the trade-offs they consider. We first conducted a survey to gain initial insights into how people balance competing priorities in scheduling and what factors influence their choices of places and transportation modes. We then conducted an interview study with hypothetical scheduling scenarios to examine how people compose schedules and what factors influence their decisions, including deviations from routines. In this section, we present the design and findings of the survey (Section 4.1) and the interview (Section 4.2), followed by the takeaways drawn from both studies (Section 4.3).

4.1 Survey

4.1.1 Study Design and Participants. The survey aimed to examine the trade-offs people value and the factors they consider when choosing places to go and transportation modes. We recruited 147 participants through campus bulletins, company bulletins, and subsequent snowball sampling. Table 1 summarizes the demographic characteristics. The survey took approximately 15 minutes, and participants received $2.30-equivalent compensation.

Table 1. Demographic characteristics of the survey and individual interview participants.

Study	Gender			Age						Occupation			
	F	M	N/A	19–29	30–39	40–49	50–59	mean (SD)	min–max	UG	Grad	OW	Other
Survey	72	65	10	105	25	8	9	29.1 (8.72)	19–57	23	63	48	13
Interview	14	4	-	16	2	-	-	24.56 (3.73)	19–33	6	9	3	-

N/A: Prefer not to say; UG: Undergraduate student; Grad: Graduate student; OW: Office worker; Other: Self-employed/researcher/teacher, etc.

The survey consisted of two parts. The full set of survey items is included in Appendix A.2. **(1) Decision Criteria.** Participants rated and ranked the criteria they consider and prioritize when choosing places or modes of transportation (e.g., convenience, familiarity, cost, physical effort). **(2) Scenario-Based Choice.** Participants were given a travel scenario—meeting a friend for dinner—and asked to choose between walking, bus, or taxi. We chose a low-constraint everyday context, minimizing situational factors (e.g., urgency, cargo, weather sensitivity) that could otherwise confound participants' responses to the information conditions. The format for presenting per-option meta-information follows prior work on eco-feedback in transportation choice interfaces [74], in which participants make repeated choices across trials with varying information conditions.

4.1.2 Findings. When choosing transportation and places, participants primarily cited self-centered, immediate factors. For transportation, the frequently selected values were short travel time (33%), travel comfort (32%), and low cost (19%). For places, participants prioritized familiarity (61%), proximity (44%), and a pleasant environment (33%). Environmental impact was rarely raised as a primary criterion in the open-ended items—only one participant mentioned carbon footprint when describing their transportation values. However, when subsequently prompted to rate their willingness to invest in carbon reduction, participants reported some willingness to act: 88% indicated some or strong willingness to invest *effort*, and 73% to invest *time*, while 65% reported the same for *money*.

4.2 Individual Interview

4.2.1 Study Design and Participants. Based on the survey findings, we designed an interview study to gain a deeper understanding of the criteria people use when making scheduling decisions. We employed hypothetical scheduling scenarios and a mobile application prototype as probes in semi-structured interviews with 18 participants. Participants were recruited through the same channels as the survey, with no overlap. Demographic characteristics are summarized in Table 1, and participants' primary transportation modes are reported in Table 14 in Appendix.

Each interview consisted of three main activities. **(1) Hypothetical Scheduling.** To directly observe participants' decision-making processes, we asked them to compose a schedule for a hypothetical day. Each participant was given an identical set of three fixed events and four flexible tasks, along with a map and transportation options. Holding the task set constant across participants allowed us to surface individual differences in how the same set of commitments is arranged. For each decision, we probed the reasoning behind each place and transportation choice, and asked follow-up questions about factors that might lead participants to revise their decisions. **(2) Schedule Comparison.** To examine how people respond to schedules composed by others, we presented six candidate schedules and asked about their preferences. The candidates were constructed by the research team using the same task set from the Hypothetical Scheduling activity. They spanned a range of carbon emissions, from carbon-minimizing to carbon-maximizing schedules, with four additional schedules in between. Participants discussed which schedules they preferred, explained their reasoning, and reflected on their willingness to follow such suggestions in practice. **(3) Interface Feedback.** To inform the user interface design of a system-driven scheduling application that suggests schedules to users, we developed a mobile prototype and asked participants to walk through it and suggest improvements. The prototype resembled a commercial calendar application, with a top-of-screen indicator displaying estimated carbon emissions for the schedule.

Interviews were conducted by two authors, in a mix of in-person and remote (video call) sessions, depending on participant availability. Each session lasted about one hour, and participants received $11-equivalent compensation. All sessions were audio recorded and later transcribed. We analyzed the interview following a reflective thematic analysis approach [15, 16]. Two researchers independently conducted inductive open coding on the transcripts, then met iteratively to refine codes and develop higher-level themes until consensus was reached.

4.2.2 Findings. Our analysis surfaced three themes on how participants reasoned about everyday plans, how they accepted system-generated suggestions, and what they expected from the system. Each theme includes two or three sub-themes. Representative codes are listed in Appendix A.4.

Theme 1: Feasibility of a plan is personal, contextual, and shifting. Feasibility was shaped by how activities were arranged across the day rather than by any single activity in isolation. As P6 explained, P6: "*It's hard to walk before work (because of sweat), but it's okay to walk after a workout (after already sweating).*" Several participants treated the overall arrangement as more decisive than any specific transport mode (P10, P15).

Beyond arrangement, feasibility depends on personal preferences and constraints. In transport, both availability and acceptability varied across participants. Walking tolerance ranged from 15 to 60 minutes, and available modes depend on residence (e.g., subway). For places, some activities were tied to a single setting (e.g., workout) while others moved across places (e.g., reading, work). Crucially, which activities were fixed or flexible also varied.

Even within the same person and the same set of options, feasibility shifted with daily states—almost everyone reported altering their decisions under rain, heat, fatigue, or company. For example, P10 cycled most days but switched to walk on rainy days, and P12 walked by default but turned to public transport when feeling unwell.

Theme 2: Acceptance of system-suggested schedules requires feasibility, not just low carbon. Carbon-minimizing schedules are rarely top-ranked. Across the six candidate schedules, the carbon-minimizing one was top-ranked by only two participants, as most participants traded off carbon impact against feasibility. They gave concrete reasons for not highly ranking the carbon-minimizing schedule. P11 found the day too packed. P15 and P18 considered the walking distances excessive.

Acceptance also fluctuated with daily state and information framing. P17 and P18 described low-carbon scheduling as feasible only on days when they had the room for it, such as when their condition and the weather aligned. For example, P18: "*It's hard to live a carbon-conscious day every day, but I can accept it on less busy days.*" Information also reshaped acceptance. Several participants noted that quantified carbon information would prompt reconsideration of their choices (P1–3, P13, P17–18).

Theme 3: Users wanted assistance that leaves the final choice to them. Participants' acceptance of planning help was conditional on retaining final authority. While some valued the planning help (P2, P9, P12), others preferred flexible plans, citing feeling forced (P10, P16) or lacking confidence in following through (P7).

Participants also wanted impact framed in terms they value, reasoning across multiple dimensions. P1 weighed time against money, and P6 explicitly described the inverse relationship of cost and time. P10 noted that framing in terms of cost savings or health benefits would be more motivating than reporting grams of carbon.

Finally, participants wanted system contributions to be visually distinguishable. Several participants wanted system-filled items, such as transportation and flexible tasks, to be visually separable from user-defined entries through different colors or shapes (P3, P11, P14, P16).

4.3 Takeaways

Synthesizing the findings above, we derived four takeaways for a system that helps carbon-aware daily planning.

- **Takeaway 1: Accommodate the heterogeneous properties of individual activities.** Our interviews showed that activities differ in what is fixed and flexible—some are tied to a specific place or time, while others

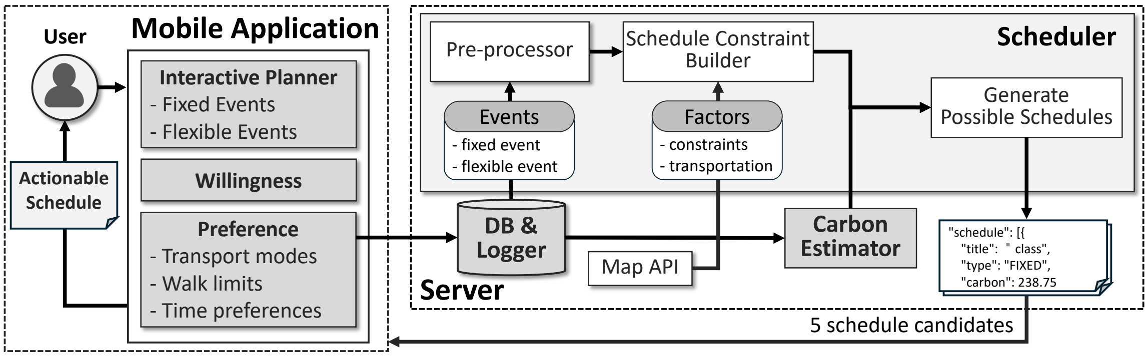


Fig. 3. An overview of the system architecture, showing how EcoTailor generates tailored daily schedules from user inputs.

can be rearranged—and this varies across participants. To generate schedules that users would consider feasible, the system must allow each activity to carry its own constraints on place, time, and flexibility.

- **Takeaway 2: Reflect user-specific conditions that vary across individuals and contexts.** Interview participants' scheduling decisions were shaped by two types of conditions: relatively stable individual differences and daily fluctuations driven by factors such as weather or fatigue. The system should accommodate both, respecting enduring constraints while adapting to the daily context.
- **Takeaway 3: Offer alternative schedules rather than a single recommendation.** The interview surfaced consistent evidence against a single-plan recommendation: preferences were dispersed, participants wanted to retain final authority, and carbon-minimizing schedules were often rejected as impractical. To accommodate shifting priorities and varying willingness, the system should offer multiple schedule options reflecting trade-offs between sustainability and convenience, allowing users to select what best fits their current situation.
- **Takeaway 4: Make trade-offs visible through salient and multi-dimensional information.** Carbon rarely operates as a top-ranked criterion in daily decisions, yet our findings suggest that surfacing carbon information at the moment of choice could shift decisions. Moreover, interview participants valued the information—e.g., cost savings or health benefits—in motivating their choices. Thus, the system should present not only carbon information for each schedule, but also other dimensions that users value.

5 ECOTAILOR

Building on the findings and takeaways from the preliminary study, we designed and implemented EcoTailor, a mobile application that helps users plan low-carbon daily schedules in real-world contexts. As shown in Figure 3, EcoTailor consists of a mobile application and a server. Users enter their daily activities and preferences through the application, and the server processes this input to generate feasible schedule candidates with varying carbon emissions, allowing users to select what best fits their situation. Below, we describe the key design features of EcoTailor (Section 5.1), followed by the mobile application (Section 5.2) and the server (Section 5.3).

5.1 Key Features

5.1.1 Four Event Types. To address **Takeaway 1**, the system needs a representation that captures the heterogeneous flexibility of daily activities—some are anchored to a specific time and place, while others afford flexibility along the time or place dimension. Reflecting the two axes along which users reason about schedules—*when* an activity must occur and *where* it must take place—we represent each event by whether its time and place are fixed by the user or left open. The axes are independently constrained across activities, yielding four types: (1) **fixed**

Table 2. Four event types and characteristics.

		WHERE to do	
		user-specified place	optimal place
WHEN to do	user-specified time	fixed event (e.g., conference)	place-flexible event (e.g., remote work)
	optimal time	time-flexible event (e.g., washing dish)	full-flexible event (e.g., reading)

events, with fixed time and place, and three types of **flexible events** — (2) **place-flexible**, (3) **time-flexible**, and (4) **full-flexible** (both time and place are flexible). Table 2 summarizes the scheduling criteria for each type.

5.1.2 Personal Preferences. Beyond per-activity constraints, **Takeaway 2** calls for reflecting user-specific conditions. We support two dimensions of *Preferences* identified in our preliminary study: (1) *time-of-day preferences*, capturing preferred periods for activities (e.g., exercising in the morning); and (2) *transport-mode preferences*, capturing available transport modes and walking tolerance (e.g., owning a bicycle or walking up to 20 minutes). These *Preferences* are relatively stable but not fixed: a user who normally cycles may avoid it in the rain. We therefore treat preferences as *modifiable defaults*—configured once but editable at any time—to accommodate daily context. Additional details are provided in Appendix A.5.

5.1.3 Willingness to Reduce Carbon. Personal preferences capture stable differences, but **Takeaway 2** also highlights a dynamic dimension: people's motivation or capacity for carbon-saving behaviors fluctuates from day to day, shaped by factors such as mood, fatigue, time pressure, or competing priorities. **Takeaway 3** further suggests that a single fixed option may limit actionability, as willingness varies with context. To address this, we abstract these factors into a single dimension, *Willingness*, representing the user's intended effort toward carbon reduction at the moment of planning. By adjusting this level, users can explore multiple schedules with different trade-offs between carbon emissions, travel time, and cost, and choose one that fits the day. This design also addresses **Takeaway 4**: each schedule is presented with its carbon, time, and cost values, so adjusting Willingness reveals both alternative schedules and their shifting trade-offs.

5.1.4 Rescheduling. The features above operate at initial schedule generation, but plans rarely unfold as expected. To reflect the contextual variation noted in **Takeaway 2**, the system must also handle mid-day changes. We therefore designed *Rescheduling* to address such unanticipated disruptions. When tasks or priorities change, users can update context and regenerate the remaining schedule to maintain feasibility throughout the day.

5.1.5 User Interface. To support familiarity, we designed EcoTailor's interface to resemble commercial calendar applications. As identified in Theme 3 (Section 4.2), users require a distinction between self- and system-scheduled events. We therefore use color coding: fixed events in green, flexible events in blue, and movements in orange.

5.2 EcoTailor Mobile Application

To support both iOS and Android, we developed the application with Flutter. The interface supports (1) setting preferences, (2) managing events, and (3) exploring schedules, as shown in Figure 4 with labels A–E.

Step 0: Preference Setting. Users set preferences such as preferred activity times, transport modes, and maximum walking time A. Users can also set daily start and end times to avoid inconvenient hours.

Step 1: Event Management. Users input fixed and flexible events. Fixed events specify start time, end time, and place B. Flexible events are managed as checklist items with a title, expected duration, and category (e.g., work, study, exercise) C. By default, they are unconstrained in both time and place, but users can constrain either to create time- or place-flexible events. Each morning, users select flexible events for that day's schedule.

Step 2: Scheduling. EcoTailor generates five schedule candidates satisfying the constraints D. Each includes fixed events, time- and place-assigned flexible events, and transport modes between places. Users browse

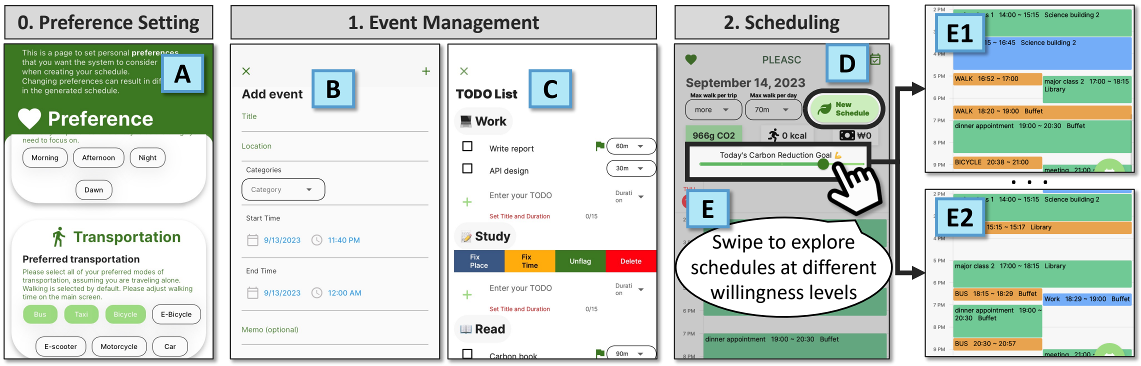


Fig. 4. The usage flow of the EcoTailor application. A Preference screen for setting time-of-day and transport modes. B Add Event screen for entering event details. C To-do List for managing flexible events and their time/place flexibility. D Calendar screen showing schedule candidates. E Willingness bar for exploring and selecting today's schedule (E1, E2).

candidates by adjusting the *Willingness* bar E, which controls the trade-off between convenience and carbon emissions. The bar has five discrete positions, each corresponding to a candidate for a different willingness level. Sliding right yields a lower-emission schedule with potentially more effort E1, while sliding left yields a less carbon-friendly one E2. For each schedule, EcoTailor presents estimated carbon emissions, exercise, and financial cost, helping users assess acceptability. Users can explore candidates by sliding the bar back and forth, observing how the schedule and its metrics change. Carbon emissions are shown numerically, following prior findings [74]. Users can request new schedules at any time if circumstances change through Rescheduling.

5.3 EcoTailor Server

As shown in Figure 3, the server comprises three components: a Scheduler, a Carbon Estimator, a Database and Logger. We describe each below. The server is implemented using NestJS (^8.0.0) and MySQL (8.1.0) with PM2 for stability, and runs on hardware of one AMD EPYC 2.8 GHz 16-core CPU and 256 GB memory.

5.3.1 Scheduler. Scheduler generates a carbon-aware schedule by formulating the daily scheduling task as a constrained optimization problem over place and transportation mode choices, as motivated in Section 1. Rather than proposing a novel algorithm, our contribution lies in formulating user-centered carbon-aware scheduling that captures (1) the trade-off between carbon savings and other user costs, (2) flexible event allocation, and (3) all temporal, spatial, and user-defined constraints. This formulation reflects findings from our preliminary study, in which users preferred to balance carbon reduction with an acceptable level of inconvenience. Accordingly, our objective of the optimization is not to identify a single carbon-minimizing schedule, but rather to generate multiple feasible schedule candidates along a spectrum of different carbon–convenience trade-offs from which users can choose. To achieve this, the formulation considers the following factors:

(i) time-ordered permutations of fixed and flexible events, fixed events occur at specified times without overlap;
(ii) place-combinations for each event, ensuring that place-fixed events occur at their designated places;
(iii) transport options between adjacent events, ensuring that travel fits within the allowed time gap;
(iv) sequence of event times, places, and transport modes that jointly minimize carbon and travel time.

Below, we describe the step-by-step formulation. Table 3 lists the notations used. Eq. (1) defines the construction of every possible $\mathbb{E}$, a time-ordered permutation of events with assigned places, satisfying criteria (i) and (ii). Note that [...] denotes an ordered permutation, {...} represents an unordered set, and $|\mathbb{X}|$ indicates its cardinality.

$$\text{Given } \mathbb{E}_{\text{fixed}} = [e_1^{\text{fixed}}, e_2^{\text{fixed}}, ..., e_j^{\text{fixed}}, ..., e_M^{\text{fixed}}], \;\; \mathbb{E}_{\text{flexible}} = \{e_1^{\text{flexible}}, e_2^{\text{flexible}}, ..., e_k^{\text{flexible}}, ..., e_K^{\text{flexible}}\},$$

Table 3. Notations of optimization formula.

Variable	Definition	Function	Definition
$\mathbb{E}_{\text{fixed}}$	Permutation of fixed events	$\mathcal{P}(e)$	Place of event e
$\mathbb{E}_{\text{flexible}}$	Set of flexible events	$\mathcal{T}_{\text{start}}(e)$	Start time of event e
$\mathbb{E}$	Permutation of $\mathbb{E}_{\text{fixed}}$ and $\mathbb{E}_{\text{flexible}}$	$\mathcal{T}_{\text{end}}(e)$	End time of event e
$\mathbb{P}_{\text{option}}$	Set of possible place options	$\mathcal{D}_{\text{event}}(e)$	Duration of event e
$\mathbb{T}_{\text{option}}$	Set of possible transportation options	$\mathcal{D}_{\text{trans}}(e_i, e_{i+1}, t_i)$	The fastest travel duration from e_i to e_{i+1} using transportation t_i
$\mathbb{T}_{\text{pref}}$	Set of user-preferred transportation options	$\mathcal{R}(e_i, e_{i+1}, t_i)$	The shortest route to move from e_i to e_{i+1} using transportation t_i
$\mathbb{T}$	Permutation of $\mathbb{T}_{\text{pref}}$	$\mathcal{CP}(e)$	Unit carbon emissions of event e
W_{trip}	Maximum walking time per single walk	$\mathcal{CT}(t)$	Unit carbon emissions of transportation t
W_{day}	Maximum total walking time per day		

$$\mathbb{P}_{\text{option}} = \{p_1, p_2, ..., p_l, ..., p_L\},$$

$$\text{We obtain } \mathbb{E} = [e_1, ..., e_i, ..., e_N], \text{ s.t. for } e_i \text{ and } e_{i+d}, \exists d \text{ that } e_i = e_j^{\text{fixed}} \text{ and } e_{i+d} = e_{j+1}^{\text{fixed}},$$
$$\text{for } d > 1, [e_{i+1}, ..., e_{i+d-1}] \in \mathbb{E}_{\text{flexible}},$$
$$|\mathbb{E}| = |\mathbb{E}_{\text{fixed}}| + |\mathbb{E}_{\text{flexible}}|, \quad \text{where} \begin{cases} \sum_{k=1}^{d-1} \mathcal{D}_{\text{event}}(e_{i+k}) \leq \mathcal{T}_{\text{start}}(e_{j+1}^{\text{fixed}}) - \mathcal{T}_{\text{end}}(e_j^{\text{fixed}}), \\ \mathcal{P}(e_k^{\text{flexible}}) = p_l \quad (p_l \in \mathbb{P}_{\text{option}}, 1 \leq l \leq L) \end{cases} \tag{1}$$

Eq. (2) constructs $\mathbb{T}$, a permutation of $N-1$ transports for $|\mathbb{E}| = N$. $\mathbb{T}_{\text{option}}$ includes a null transport ($\emptyset$) for adjacent events at the same place. All transport modes should align with user preferences. For each transport option, we use travel duration estimates from the TMap Transit API [4], including walking time to public transit stops. However, these are deterministic estimates and do not account for stochastic deviations such as bus delays or missed connections. We discuss this limitation and potential extensions in Section 8.3.

$$\mathbb{T} = [t_1, t_2, ..., t_i, ..., t_{N-1}], \ \mathbb{T}_{\text{option}} = \{\emptyset, \text{WALK}, \text{BUS}, ..., \text{CAR}\} \quad \text{where } \ \mathbb{T}_{\text{pref}} \subset \mathbb{T}_{\text{option}}, \forall t_i \in \mathbb{T}, t_i \in \mathbb{T}_{\text{pref}} \tag{2}$$

Now, Eq. (3) returns the optimal choices of $\mathbb{E}$ and $\mathbb{T}$ (i.e., schedule) that minimizes gross carbon for the day.

$$\underset{\mathbb{E},\mathbb{T}}{\text{argmin}} \sum_{e\in\mathbb{E}}^{\mathbb{E}} \mathcal{CP}(e)\cdot\mathcal{D}_{\text{event}}(e) + \sum_{e\in\mathbb{E},t\in\mathbb{T}}^{\mathbb{E},\mathbb{T}} \mathcal{CT}(t)\cdot\mathcal{R}(e_i, e_{i+1}, t_i) + \lambda \left| \sum_{e\in\mathbb{E},t\in\mathbb{T}}^{\mathbb{E},\mathbb{T}} \mathcal{D}_{\text{trans}}(e_i, e_{i+1}, t_i) \right|$$
$$\text{where} \begin{cases} \mathcal{D}_{\text{trans}}(e_i, e_{i+1}, t_i) \leq \mathcal{T}_{\text{start}}(e_{i+1}) - \mathcal{T}_{\text{end}}(e_i) \\ \forall t_i = \text{WALK} \in \mathbb{T}, \mathcal{D}_{\text{trans}}(e_i, e_{i+1}, t_i) \leq \text{W}_{\text{trip}} \\ \forall t_i = \text{WALK} \in \mathbb{T}, \sum \mathcal{D}_{\text{trans}}(e_i, e_{i+1}, t_i) \leq \text{W}_{\text{day}} \end{cases} \tag{3}$$

Note that $\lambda|\cdot|$ in argmin serves as a regularization term capturing the user's willingness, controlling the trade-off between carbon emissions and travel time: higher willingness corresponds to a smaller λ, prioritizing carbon savings. To keep computation tractable, we apply heuristics to narrow the solution space (e.g., assuming the user starts and ends at home, and co-locating flexible events with nearby fixed events). Schedule generation typically completes within a minute. The full pipeline, including solver details, is in Appendix A.7.

During development, we iteratively refined the Scheduler using sample schedule sets. People not involved in the project looked over the generated schedules and provided feedback on whether they seemed realistic. We also examined example schedules from our system alongside carbon-minimizing ones, confirming that our Scheduler produced the multiple trade-offs we intended (Appendix A.6).

5.3.2 Carbon Estimator. To estimate total carbon emissions, the Scheduler uses unit carbon values for both events and transportation derived from available statistical datasets. Note again that developing a carbon estimation model or improving the accuracy of carbon emission values is beyond our scope; these are independent external sources that can be plugged into our system. As more estimation models evolve and datasets are released, our system can integrate them to improve estimation quality. Table 12 in Appendix A.1 presents carbon emission examples for transport modes and place types.

For transportation, we use per-passenger emissions per unit distance, incorporating both direct and lifecycle emissions [3, 43, 67, 85, 98]. For place, we estimated emissions based on electricity consumption data, with granularity varying by data availability. For on-campus buildings, we used data from our administration, including electricity usage, floor area, the number of rooms and floors. For third-party places, we relied on national statistics [5] on average electricity consumption by place type (e.g., residence, office). Electricity use was converted to carbon emissions based on the amount of carbon released to generate 1 kW of electricity (474.7 gCO_2/kWh) [2]. We acknowledge that both estimates rely on category- or population-level averages and abstract away instance-specific variations. For transportation, the per-passenger factors assume the average vehicle occupancy reported in the source statistics rather than the actual number of co-passengers on a given trip. For places, the per-category electricity statistics cannot capture facility-specific differences or how occupancy at the time of visit affects the per-person footprint. We discuss the implications of this abstraction further in Section 8.3.

5.3.3 Database & Logger. The database stores both dynamic data (e.g., preferences, events, usage logs) and static data (e.g., unit carbon emissions). To better integrate scheduling logic, we implemented a custom calendar module instead of using third-party APIs such as Google Calendar. At the time of implementation, most commercial services handled calendar and to-do items separately, while our system requires a unified model that combines calendar events (fixed events) and to-do items (flexible events).

6 SCENARIO-BASED IN-LAB STUDY

As EcoTailor combines carbon reduction with scheduling support, it is important to examine whether this approach leads to lower-carbon schedules compared to providing carbon-related information alone, and how such suggestions are perceived in terms of feasibility and acceptability. To address these questions under controlled conditions, we conducted a scenario-based in-lab study comparing EcoTailor with an Awareness-raising Condition as a baseline. We describe the study design and conditions (Section 6.1), procedure (Section 6.2), participant demographics (Section 6.3), data being collected and analyzed (Section 6.4), and results (Section 6.5).

6.1 Study Design

We employed a between-subject design, assigning participants to either the EcoTailor Condition or the Awareness-raising Condition. A between-subjects approach was chosen because prior scheduling decisions and carbon feedback could carry over and systematically influence how subsequent schedules were constructed. The two conditions were designed as follows:

- **EcoTailor Condition:** the full system described in Section 5, implemented as a mobile application.
- **Awareness-raising Condition (baseline):** a mobile application sharing the same UI style as EcoTailor to minimize confounds. After participants enter a schedule, the application displays its estimated carbon emissions and presents carbon-reduction tips drawn from established environmental guidance (e.g., *"leave your car at home and walk or cycle when possible"* [1]). Unlike EcoTailor, it does not suggest tailored schedules.

The study consisted of two day-planning tasks. In *Self-based Day Planning*, participants first scheduled their own typical day without any system assistance, and then scheduled the same day again using their assigned system (either EcoTailor or the Awareness-raising Condition). The former schedule served as a baseline for comparing the difference in carbon emissions between the two schedules. In *Persona-based Day Planning*, participants scheduled a day for a given persona using their assigned system. Since all participants started from the same persona profiles, this design allowed direct comparison of absolute carbon emissions across conditions.

For *Persona-based Day Planning*, we constructed three personas representing varying levels of daily flexibility, defined by the number of fixed events. Flexible activities (e.g., focused work, exercise, meals) were drawn from the American Time Use Survey [94] to reflect realistic daily patterns. Table 4 summarizes these personas.

Table 4. Three personas constructed for Persona-Based Day Planning, varying in schedule flexibility based on the number and structure of fixed commitments.

Persona	Flexibility	Occupation	Schedule Structure
Persona A	Low	Office worker with childcare	Weekday office hours (9 AM–5 PM); child pickup at a fixed time; morning preparation and family dinner at home
Persona B	Medium	Hybrid worker	Morning video meeting at home; lunch meeting in town
Persona C	High	Freelancer	Accompanying a parent to a medical appointment

Two methodological challenges shaped our design. First, schedules constructed in an in-lab setting may not reflect what participants would actually carry out in daily life. To address this gap, we drew on the Theory of Planned Behavior (TPB) [6, 8], measuring both behavioral intention and behavioral expectation. Behavioral intention captures one's conscious plan to perform a behavior, while behavioral expectation reflects one's self-prediction of whether one will actually do so, considering all factors [97]. Second, *Persona-based Day Planning* requires participants to immerse themselves in each persona's situation. We therefore introduced each persona in detail before the task, asking participants to reason and decide from the persona's perspective. We also collected validation measures to verify whether participants understood and immersed themselves in the personas.

6.2 Study Procedure

The study consisted of the following four phases.

Introduction & System Familiarization. Participants were briefed on the study's purpose and procedure. Next, they were introduced to their assigned system. The experimenter walked them through the system's interface and core features, after which participants were given time to freely explore the system.

Self-based Day Planning. Participants constructed a schedule for their own typical weekday. First, using a custom drag-and-drop web tool, they captured their typical routine ($\text{Schedule}_{\text{usual}}$) as a baseline. The same tool was used across both conditions to ensure consistency. They then constructed it again using their assigned system ($\text{Schedule}_{\text{system\_initial}}$). As $\text{Schedule}_{\text{system\_initial}}$ may reflect an idealized plan rather than what participants would realistically follow, they completed the TPB survey and were asked to reflect on what elements should change for the schedule to be realistically lived out, and to revise accordingly. The resulting schedule ($\text{Schedule}_{\text{system}}$) served as the basis for the carbon emissions calculation. Measures included carbon emissions (percentage difference between $\text{Schedule}_{\text{usual}}$ and $\text{Schedule}_{\text{system}}$), task completion time, and behavioral intention and expectation (TPB).

Persona-based Day Planning. Participants embodied three personas and constructed a full-day schedule for each, based on a given set of activities, with counterbalancing the order of each persona being presented. This phase provided a more controlled setting for directly comparing carbon outcomes across conditions, and allowed us to indirectly observe system effects across a wider range of demographic and situational contexts. As in the *Self-based Day Planning* phase, participants completed the TPB survey after constructing each schedule and revised it to what they could realistically follow. Measures included carbon emissions (absolute values of finalized schedules), task completion time, behavioral intention and expectation (TPB), and persona understanding (occupation recognition, perceived schedule flexibility, and Persona Perception Scale [86]).

Post-Study Survey & Interview. Upon completing both phases, participants filled out a post-study survey. Measures included system evaluation via System Usability Scale (SUS) [18], NASA-TLX [40], and Hedonic TAM

(PU, PEOU, ITU, and PE) [95, 96]. A brief semi-structured interview followed, covering overall experience, burden of data entry, and suggestions for improvement.

6.3 Participants

We recruited 38 participants (19 per condition) through university bulletin boards. Eligibility was restricted to individuals who regularly use a digital calendar for schedule management. Participants received $15-equivalent compensation upon completion of the 90-minute session. Participants were assigned to conditions through stratified allocation, balancing key demographic variables (gender, occupation, and car ownership) while also ensuring comparable distributions of daily carbon emissions and environmental concern (YPCCC scale [63]) across the two groups. The resulting variance ratio of daily carbon emissions between the two conditions was 1.06, indicating comparable distributions. Table 5 summarizes the demographics of participants in each condition.

Table 5. Demographic characteristics of participants by condition.

System Condition	Gender		Age		Occupation				Car		YPCCC
	M	F	mean (SD)	min–max	UG	Grad	Emp	Other	Yes	No	mean (SD)
Awareness-raising	8	11	24.32 (3.20)	19–31	5	13	0	1	4	15	5.29 (0.52)
EcoTailor	6	13	24.42 (3.25)	19–33	5	12	1	1	4	15	5.10 (0.64)

UG: Undergraduate student; Grad: Graduate student; Emp: Employee; Car: Car ownership; YPCCC (7-point Likert scale).

6.4 Data Analysis

For the collected data, we applied the analysis methods in Table 6. Below we elaborate on carbon emission data.

Comparison of carbon emissions between conditions. To assess the effect of EcoTailor's carbon-aware scheduling compared to carbon information alone, we compared constructed schedules between conditions. Because participants differ in their typical daily carbon emissions, the *Self-based Day Planning* phase reports the *percentage change* from each participant's own baseline schedule, normalizing for these individual differences. In the *Persona-based Day Planning* phase, participants created schedules for a fixed persona rather than for themselves, so no personal baseline exists. Since all participants faced an identical scheduling context, we instead compare *absolute* carbon emissions (gCO_2) directly between conditions.

We tested a null hypothesis (H_0) that the two conditions do not differ meaningfully in carbon emissions, against an alternative hypothesis (H_1) that EcoTailor is associated with lower carbon emissions than the Awareness-raising Condition. Comparisons used Mann-Whitney U tests, selected for robustness to non-normal distributions in our sample. We treated each comparison as independent and did not apply multiple-comparison corrections.

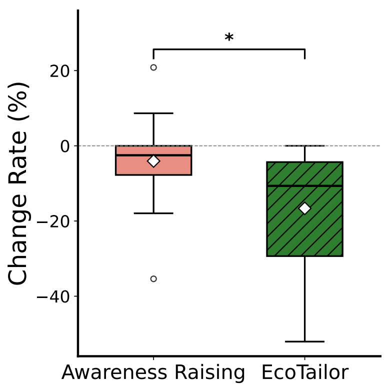
6.5 Results

6.5.1 Self-based Carbon Emissions. In the *Self-based Day Planning* phase, we compared estimated daily carbon emissions from one's $\text{Schedule}_{\text{system}}$ against their own $\text{Schedule}_{\text{usual}}$. Participants in the EcoTailor Condition showed an average reduction of daily emissions by 16.64%, while those in the Awareness-raising Condition showed an average reduction by 4.05% (p = .033). Figure 5a illustrates this result, with detailed values in Table 7. These reductions reflect finalized schedules—revised by participants after the TPB survey to align with what they could realistically follow. Notably, more participants in the EcoTailor Condition (13 of 19) revised their schedules after the TPB survey than in the Awareness-raising Condition (4 of 19). Most revisions in the EcoTailor Condition reverted suggestions that did not fit participants' usual routines, often transportation choices. Behavioral intention (BI) scores were similarly high across conditions. Behavioral expectation (BE) tended to be lower in the EcoTailor Condition, explaining the higher revision rate observed above. Full BI and BE values are reported in Table 18 in Appendix.

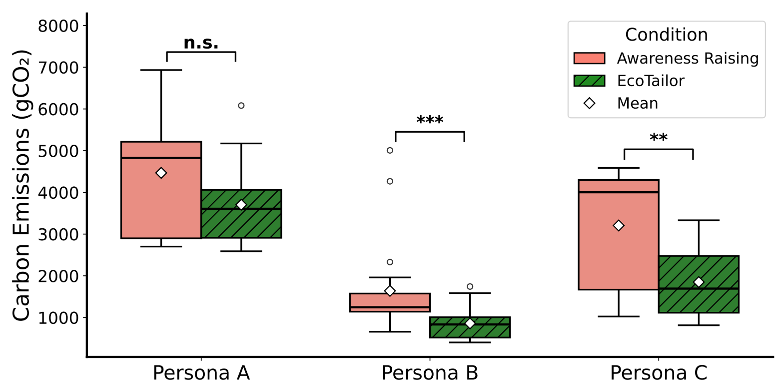
Table 6. Overview of data collected during the scenario-based in-lab study, with corresponding analysis methods.

Data	How Collected	When Collected	Purpose	Analysis
Carbon emissions (Self-Based)	Estimated from constructed schedules	Self-Based Day Planning	Compare carbon emissions between conditions, relative to each participant's baseline	Mann-Whitney U
Carbon emissions (Persona-Based)	Estimated from constructed schedules	Persona-Based Day Planning	Compare absolute carbon emissions between conditions, per persona	Mann-Whitney U (per persona)
Task completion time	Recorded during sessions	Both Day Planning task	Compare effort required to construct schedules between conditions	Mann-Whitney U
Persona understanding	Occupation recognition, perceived flexibility, Persona Perception Scale	Persona-Based Day Planning	Verify persona design and immersion across conditions	Exclusion check, response tendency
System evaluation	SUS, NASA-TLX, Hedonic TAM (PU, PEOU, ITU, PE)	Post-study survey	Evaluate usability, workload, and perceived acceptance	Multiple*
Overall experience	Brief semi-structured interview	Post-study	Provide qualitative context for findings	Qualitative review

*SUS: SUS score analysis; NASA-TLX: Mann-Whitney U; Hedonic TAM: response tendency analysis.



(a) Percentage change in estimated daily emissions before vs. after system use.



(b) Absolute daily emissions under fixed personas. Boxplots show the median and interquartile range, with diamonds indicating the mean.

Fig. 5. Comparison of carbon emissions between EcoTailor Condition and Awareness-raising Condition for (a) a self-selected day and (b) predefined persona days (*$p < .05$, **$p < .01$, ***$p < .001$; n.s. = not significant).

6.5.2 *Sources of Carbon Reduction.* To understand the sources of reduced carbon emissions in the *Self-based Day Planning* phase, we additionally analyzed the differences between each participant's $\text{Schedule}_{\text{usual}}$ and $\text{Schedule}_{\text{system}}$ in both conditions. We identified two recurring patterns of change:

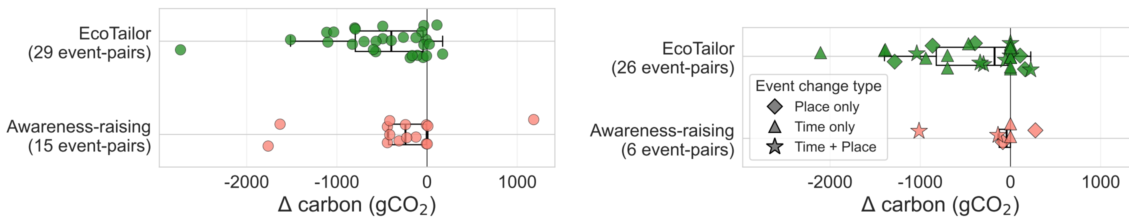
① **Transport-oriented changes:** Switching to a low-carbon transportation mode while keeping the original event's time and place unchanged (e.g., driving → public transit for the same commute).

② **Event-oriented changes:** Reorganizing the event itself to enable lower-carbon outcomes, in one of three forms: (1) shifting the event to a different place where the activity itself produces less carbon, (2) shifting the event to a different time so that lower-carbon transportation modes become feasible, or (3) both.

Figure 6 shows the carbon emission change associated with each type of schedule modification. For transport-oriented changes, participants in the EcoTailor Condition made 29 changes, totaling a reduction of −11.5 kg CO_2, while those in the Awareness-raising Condition made 15, totaling −4.8 kg CO_2. For event-oriented changes, participants in the EcoTailor Condition made 26 changes, totaling −11.5 kg CO_2, while those in the Awareness-raising Condition made only 6, totaling −1.0 kg CO_2. This suggests that EcoTailor's active rearrangement of events may have widened the space to feasibly accommodate lower-carbon options, surfacing alternatives

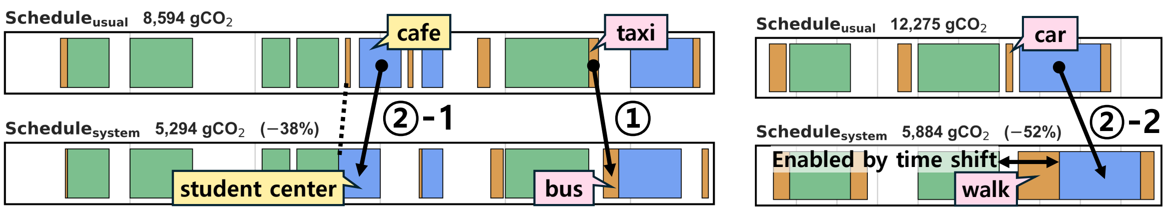
Table 7. Carbon emissions by scheduling task and condition. For the *Self-Based* task, values represent the percentage change from each participant's own baseline schedule (negative = reduction). For *Persona-Based* tasks, participants scheduled for a fixed persona rather than for themselves, so no personal baseline exists; values therefore represent absolute daily emissions (gCO_2) compared between conditions. p-values are from Mann–Whitney U tests.

Scheduling Task	**Unit**	**Awareness-raising Condition** *M (SD)*	**EcoTailor Condition** *M (SD)*	p
Self-Based	% change	−4.05 (11.34)	−16.64 (16.44)	.033
Persona A	gCO_2	4467.75 (1325.53)	3704.44 (885.49)	.08
Persona B	gCO_2	1640.18 (1129.88)	859.47 (379.26)	<.001
Persona C	gCO_2	3206.55 (1336.33)	1850.61 (851.79)	.002



(a) Carbon change from transport-oriented changes. (b) Carbon change from event-oriented changes.

Fig. 6. Carbon change per modification by condition, separated into (a) transport-oriented and (b) event-oriented changes. Each point represents a change of a single event. Vertical jitters are introduced for visibility, not to mean a new dimension.



(a) Transport-oriented change (①: taxi → bus) and a place-based event change (②-1: cafe → student center) (P32). (b) Time-based event change (②-2: shifted to a later time) that made walking feasible (P11).

Fig. 7. Examples of schedule changes that reduced daily carbon emissions in the EcoTailor Condition. Numbered markers correspond to the change categories defined in the main text.

that participants might not have considered on their own. On the other hand, the Awareness-raising Condition appears to encourage switching the transportation modes within the existing schedule, but less likely to create further room by actively rearranging the events.

Figure 7 illustrates two example schedules from the EcoTailor Condition that show how these changes took shape from $\text{Schedule}_{\text{usual}}$ to $\text{Schedule}_{\text{system}}$. In Figure 7a, P32's schedule underwent two changes. First, an afternoon study session originally planned at a cafe was relocated to the on-campus student center (②-1). This reduced emissions both from the activity itself, owing to the lower-carbon place, and from removing the trip that became unnecessary. Second, the trip home from a later outing, originally by taxi, was replaced with bus (①). In Figure 7b, P11's evening event was shifted to a later time (②-2), which made walking feasible in place of the original car trip—an option that would not have been available at the original time. Together, these examples illustrate how EcoTailor appeared to support not only transportation alternatives but also event-level reorganizations that opened up new lower-carbon options.

6.5.3 Persona-Based Carbon Emissions. In the *Persona-based Day Planning* phase, the EcoTailor Condition produced significantly lower emissions than the Awareness-raising Condition for Persona B (47.6% reduction, $p < .001$) and Persona C (42.3% reduction, $p = .002$). For Persona A, the 17.1% reduction did not reach statistical significance ($p = .08$). Figure 5b and Table 7 present these results. The non-significant result for Persona A points to a practical boundary of tailored scheduling. Among the three personas, Persona A had the most fixed commitments, with little temporal or modal flexibility in the daily routine. When a day is already tightly constrained by external obligations, the space for carbon-reducing substitutions shrinks considerably.

Behavioral intention and expectation scores were similarly high across conditions for all three personas, with full values reported in Appendix A.8. As a manipulation check, all participants correctly identified each persona's occupation, and perceived schedule flexibility for each persona aligned with our intended flexibility levels similarly across conditions, indicating that participants interpreted the personas in line with the design intent. Detailed results are reported in Table 21 in Appendix.

6.5.4 Task Completion Time. We compared the time participants took to construct each schedule, measured from the start of the task to the submission of the finalized schedule. Across all four scheduling tasks, participants in the EcoTailor Condition completed their schedules in roughly half the time required by the Awareness-raising Condition (all $p < .001$), indicating that the tailored scheduling support in EcoTailor reduced interaction cost rather than adding to it. Detailed values are reported in Table 19 in Appendix.

6.5.5 System Usability, Workload, and Acceptance. We evaluated the system across three dimensions: usability (SUS), workload (NASA-TLX), and acceptance (Hedonic TAM). The EcoTailor Condition scored 72.89 on the SUS, exceeding the benchmark for above-average usability (68[1]), while the Awareness-raising Condition scored 67.37, just below the benchmark. NASA-TLX overall workload was lower in the EcoTailor Condition ($M = 6.53$) than in the Awareness-raising Condition ($M = 8.81$), and the difference was significant ($p = .044$), suggesting that EcoTailor's proactive scheduling support reduced the cognitive effort of constructing schedules. Hedonic TAM scores (PU, PEOU, ITU, PE) were similar across conditions, with full values reported in Table 20 in Appendix.

6.5.6 Qualitative Findings. Across the post-study interviews, participants reported that using EcoTailor did not add substantial effort on top of routine schedule entry. Several noted that the experience felt comparable to or even lighter than their usual scheduling tools (P5, P11, P13, P15, P26, P28–29, P32–34, P36). Many also valued the EcoTailor's role in proposing schedule arrangements directly, describing it as a way to offload decision-making (P13, P29, P23, P25, P36–37). A few participants further noted that the suggestions led them to consider transportation modes they would not have otherwise (P4, P11, P28, P34). At the same time, several participants expressed a desire for finer control over the EcoTailor's suggestions, particularly the ability to fix specific transportation modes or events while letting the system rearrange the rest (P15, P17, P28, P32, P34).

7 IN-THE-WILD DEPLOYMENT STUDY

Building on the preceding in-lab study, we next explored how EcoTailor operates in everyday lives through a four-week in-the-wild deployment study. We describe the study design (Section 7.1), procedure (Section 7.2), participant demographics (Section 7.3), and data analysis methods (Section 7.4), followed by the findings (Section 7.5).

7.1 Study Design

We adopted a within-subject design, in which each participant went through two consecutive periods: a two-week Observation Period followed by a two-week EcoTailor Period. Given the substantial individual variability in daily routines, we chose this design so that each participant could serve as their own baseline, comparing their

[1]A SUS score over 68 is considered above average [27, 66].

EcoTailor Period against their own Observation Period. We did not counterbalance the order of the periods, as the Observation Period was intended to capture each participant's natural routine prior to any influence from EcoTailor, serving as a baseline for the subsequent analysis. The two periods were designed as follows:

- **Observation Period (2 weeks):** Participants lived their days as usual, following their typical scheduling practices, such as using calendar apps, planner books, or no explicit planning. This period aimed to capture each participant's ordinary routines without any system influence.
- **EcoTailor Period (2 weeks):** Participants used EcoTailor in their daily lives, reviewing system-generated schedules and adjusting them to fit their current situations.

Across both periods, participants completed a daily activity journal recording the type, place, and duration of activities in 30-minute intervals. We initially considered automated tracking tools but found their detection of transportation modes and activity places insufficiently reliable for our purposes.

7.2 Study Procedure

The four-week study consisted of five phases, structured around the two periods described above.

Pre-Study Interview. Before the study began, the researchers met each participant for a 30-minute session to introduce the overall study procedure, explain the activity journaling protocol, and answer any questions.

Observation Period (2 weeks). Participants lived their days as usual while completing the daily activity journal through a Google Sheets form. Each entry took approximately 10 minutes per day. Participants were asked to complete the entry by the end of each day; if they missed a day, they were reminded via text message the following morning and asked to fill it before the memory faded. From the recorded transportation modes and activity places, we estimated each participant's baseline daily carbon emissions, which served as the reference point for later comparison with the EcoTailor Period. Weekly 30-minute semi-structured interviews were conducted to discuss participants' routines and journaling experience.

Transition: Carbon Perception Survey & Training. Before moving on to the EcoTailor Period, participants completed a carbon perception survey assessing their awareness of carbon emissions and global warming, using a subset of questions from the YPCCC survey [63]. Afterward, the researchers explained how to use EcoTailor and ensured that each participant could use it confidently.

EcoTailor Period (2 weeks). Participants used EcoTailor in their daily lives while continuing to complete the activity journal. Application usage logs were also collected to capture how participants used EcoTailor's features. Weekly 30-minute semi-structured interviews were conducted to elicit participants' evolving responses to the system-suggested schedules, their sense of autonomy, and their experiences using EcoTailor.

Post-Study Survey & Exit interview. Upon completion of the EcoTailor Period, participants completed the carbon perception survey again. They also completed a post-experiment survey, including the SUS and questions on the perceived appropriateness of EcoTailor. A 30-minute exit interview followed, covering overall experience with EcoTailor, perceptions of individual features, and suggestions for improvement.

7.3 Participants

We initially recruited 20 participants through campus bulletins and word-of-mouth. In the spirit of in-the-wild study, we did not control their daily routines. While some variation in participants' routines was expected across the study period, we considered this inherent to real-life settings and continued with the original design.

Even so, a certain level of routine consistency was necessary to ensure meaningful comparison between periods. The weekly interviews included questions about any unusual events or disruptions to participants' routines. Among 20 participants, we early-stopped 2 due to drastic, unexpected, and involuntary disruptions reported in these interviews. One was quarantined due to COVID-19, while the other started a new job at a high-energy research facility in the middle of the study, resulting in a marked difference in place-origin carbon emissions between the Observation and EcoTailor Periods. The remaining 18 participants completed the four-week study without such disruptions, and Section 7.5.1 further examines their schedule comparability quantitatively. Table 8 summarizes their demographics. Each participant received compensation equivalent to $90.

Table 8. Demographic characteristics of the deployment study participants.

Gender		Age		Occupation				Smartphone OS	
M	F	mean (SD)	min–max	Undergraduate	Graduate	Office worker	Researcher	iOS	Android
9	9	24.78 (4.86)	19–37	6	9	2	1	8	10

7.4 Data Analysis

We analyzed the data using the methods in Table 9. Below we describe those that require further elaboration.

Paired test on carbon emissions. To explore whether EcoTailor influences participants' daily carbon emissions, we framed our analysis with a null hypothesis (H_0) that EcoTailor does not affect daily carbon emissions and an alternative hypothesis (H_1) that EcoTailor is associated with reduced daily carbon emissions. Daily carbon emissions were estimated from each participant's activity journal based on the recorded transportation modes and activity places, then compared between the Observation Period and EcoTailor Period.

Reflective thematic analysis on interviews. All interview recordings were transcribed and analyzed using reflective thematic analysis [15, 16, 90]. Three researchers independently performed inductive coding, followed by iterative discussions to reach a consensus. This process surfaced key themes: perceptions of EcoTailor, adoption and impact of its features, attitudes toward carbon feedback, and sense of autonomy.

Table 9. Overview of data collected during the four-week deployment study, with corresponding analysis methods.

Data	How Collected	When Collected	Purpose	Analysis
Daily carbon emissions	Daily activity journal (Google Sheets)	Both periods	Estimate daily emissions from reported transportation and places	Wilcoxon Signed-Rank Tests
Carbon perception	YPCCC subset survey	Before & after EcoTailor Period	Examine possible changes in carbon awareness	Wilcoxon Signed-Rank Tests
Application usage	Automatic logging	EcoTailor Period	Observe feature adoption and usage patterns over time	Usage frequency per participant
Overall experience	30-min semi-structured interview	End of week 3, After EcoTailor Period	Understand experience and feedback across the deployment	Reflective thematic analysis
Perceived appropriateness	Self-developed appropriateness questions	After EcoTailor Period	Evaluate perceived appropriateness of EcoTailor	Response tendency analysis
Usability	SUS	After EcoTailor Period	Evaluate system usability	SUS score analysis

7.5 RESULTS

7.5.1 Dynamics of Carbon Emissions and Perceptions.

Schedule Similarity Between Periods. Building on the routine consistency screening described in Section 7.3, we additionally examined how similar the remaining 18 participants' schedules were across the two periods. Because EcoTailor is designed to suggest times and places for flexible events, some schedule differences between the two periods are expected as part of its intended effect. We therefore focused on aspects of participants' daily routines that EcoTailor does not directly influence: daily sleep hours, number of events per day, work/study hours, and leisure hours. Applying paired two one-sided tests (TOST), we found that all four variables were equivalent within modest bounds: sleep and events per day fell within ±10% of the Observation Period mean (p = .009 and p = .040), work/study hours within ±15% (p = .032), and leisure hours within ±20% (p = .027). Although day-to-day routines naturally fluctuate in in-the-wild deployments, the variation observed here appears unlikely to have meaningfully affected the carbon emission comparison between the two periods.

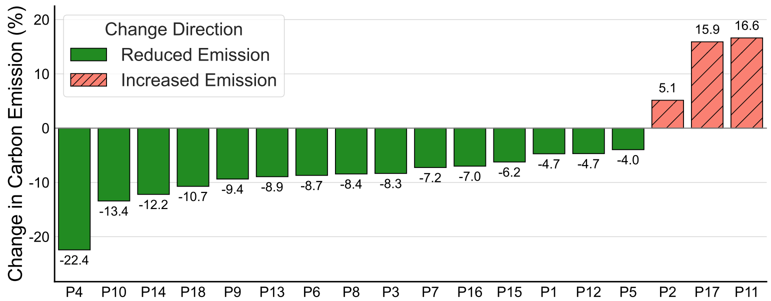
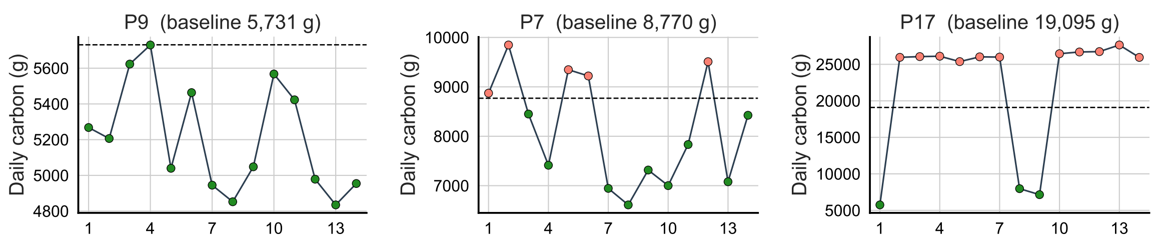


Fig. 8. Change in per-participant carbon emission between EcoTailor and Observation Period. Negative values mean decreased emissions during.

Table 10. Changes in daily carbon emissions during the EcoTailor Period relative to each participant's Observation Period, with Wilcoxon signed-rank test results.

Change in daily carbon (%)			
Best	Worst	Mean	Median
−22.42	+16.63	−5.48	−7.80

Wilcoxon signed-rank test		
n	W	p
18	36.00	0.030



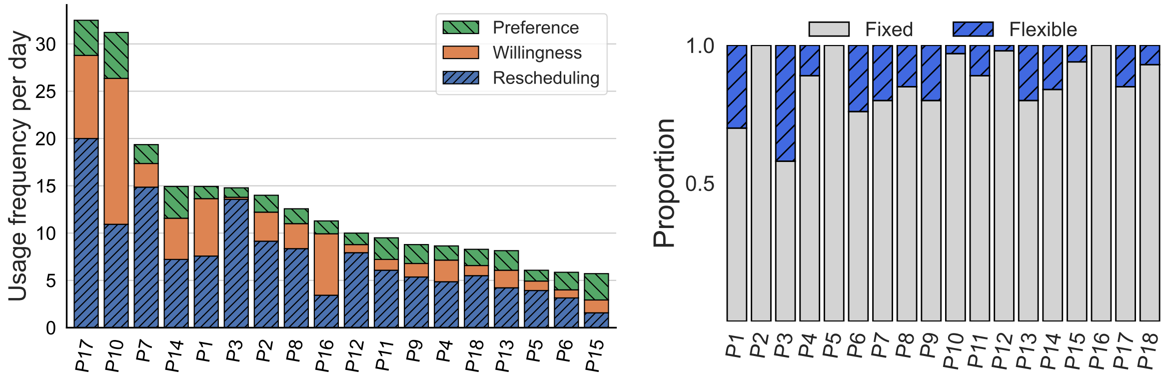
(a) Consistent reduction (P9; −9.4%). (b) Fluctuating reduction (P7; −7.2%). (c) Increase in emissions (P17; +15.9%).

Fig. 9. Daily carbon emission trajectories of three participants illustrating distinct patterns of within-participant variability during the EcoTailor Period. Each panel shows one participant's daily carbon emissions (gCO_2), with the dashed line indicating the participant's Observation Period mean as a personal baseline (annotated in each title).

Individual Carbon Emission Differences. To examine the effect of EcoTailor on individual carbon emissions, we compare each participant's mean daily carbon emissions during the Observation Period and the EcoTailor Period. As the normality test indicates non-normality, we use the Wilcoxon Signed-Rank Test for analysis. The result shows a significant decrease in daily carbon emissions during the EcoTailor Period ($p = 0.03$). Participants' emissions decrease by 5.48% on average, as illustrated in Figure 8.

While most participants show a decrease in carbon emissions during the EcoTailor Period ($N = 15$), a few participants exhibit an increase ($N = 3$). To understand these cases, we compare their schedules between periods and identify the following potential reasons. P2's weekend emissions increased because they met friends more frequently during the EcoTailor Period ($0 \longrightarrow 2$ days), resulting in more car trips. P11 also used their car more often. In the interview, P11 mentioned that EcoTailor made them more aware of the need to reduce car use, but long travel times by bus (over an hour compared to a 20-30 minute drive) and the need to carry heavy items made driving unavoidable. For P17, their working hours were extended by an hour during the EcoTailor Period, and P17's workplace happened to be of exceptionally high emissions. As a result, this one-hour extension dominated their mean daily emissions to rise during the EcoTailor Period.

Day-to-Day Carbon Trajectories During Deployment. Beyond the period-level comparison, we examine each participant's daily carbon trajectory during the EcoTailor Period relative to their Observation Period mean. As shown in Figure 9, three patterns emerge. A small subset of participants ($N = 3$; P3–4, P9) remained below their baseline on most days of the deployment (Figure 9a). The majority of participants ($N = 12$) exhibited day-to-day fluctuation around their baseline while still achieving an overall reduction (Figure 9b). Figure 9c shows P17, one of the three participants whose daily carbon increased during the EcoTailor Period; the trajectory illustrates



(a) Usage frequency for Preference, Willingness, and Rescheduling. (b) Proportion of the fixed and flexible events.

Fig. 10. Per-participant usage of EcoTailor during the deployment study.

the pattern discussed earlier, with elevated emissions on weekdays driven by their high-carbon workplace and lower emissions on weekends. Overall, these trajectories show that daily carbon emissions during the EcoTailor Period varied with each participant's day-specific circumstances, showing emissions lower than the baseline on some days and higher on others. The complete set of per-participant trajectories is provided in Appendix A.11.

Changes in Carbon Perception. The analysis of carbon emissions alone cannot fully explain whether the observed reduction stems from EcoTailor itself or from participants' heightened carbon awareness that led them to make more low-carbon choices. Therefore, we analyzed survey response regarding participants' carbon perception collected before and after the EcoTailor deployment. We conducted paired Wilcoxon Signed-Rank Tests for each survey item, followed by Bonferroni correction to control for multiple comparisons. The full questionnaire and corresponding pre-post results are provided in Table 23 in Appendix A.10.

Most survey items did not show statistically significant changes after using EcoTailor, indicating that participants' overall awareness and attitudes toward carbon and climate issues remained stable. The only item showing a significant difference was *"I believe that an individual's actions cannot make any difference in reducing carbon emissions."* The mean score for this item decreased after using EcoTailor, suggesting that participants became more likely to believe that individual actions can make a difference in reducing carbon emissions. Taken together with the observed reduction in actual carbon emissions, this result suggests that EcoTailor likely contributed to promoting carbon-efficient schedules acceptable by the participants, rather than influencing their overall carbon-awareness which might have indirectly yielded pro-carbon behaviors.

7.5.2 Overall System Usage.

Distribution of Event Types. We first analyzed the distribution of events that participants entered during the EcoTailor Period. Over the two-week period, a total of 941 events were recorded, consisting of 827 fixed events and 114 flexible events. Figure 10b shows the proportion of event types for each participant. On average, fixed events accounted for 87% of all entries, while flexible events accounted for 13%.

Key Feature Usage Patterns and Roles. We collected 3,312 usage logs of key features during EcoTailor deployment: 58% for Rescheduling, 26% for Willingness, and 16% for Preferences. Figure 10a shows the daily usage frequency per participant. Our interviews helped us further derive insights into how participants actually leveraged these features in their daily routines, as summarized below.

- **Preference plays an important role in reflecting users' current situations.** Preferences were generally set early and rarely changed, though some participants made occasional adjustments—for instance, adding taxis on busy days (P7–8) or modifying possible transport modes based on their morning condition (P10).
- **Willingness enables users to obtain schedules that better represent their motivation or intention for the day.** Willingness was used to explore the trade-off between effort and sustainability. Participants appreciated the feature for several reasons: (1) helping them understand the carbon impact of different choices by showing how schedules changed with each adjustment; (2) giving them a sense of control over how much effort they were willing to invest; (3) increasing their sense of responsibility, as the final schedule reflected their decisions rather than being imposed by the system. Notably, P6: "*I liked adjusting Willingness made the means of transport change. (...) When I found two schedules (at different Willingness levels) shown to take a similar amount of time, I chose the least-carbon one.*" Some participants also noted that setting it too high reduced actionability. P15: "*At maximum Willingness, the suggested schedule often seemed not doable. So I usually set it at 4.*" Others mentioned feeling guilty about lowering it, and tried to keep it above the midpoint (P2, P15).
- **Rescheduling helps users adjust their daily plans to accommodate changes throughout the day.** P6: "*Sometimes I suddenly came up with a new schedule in the afternoon, so I added it and regenerated my schedule in the middle of the day.*" Some participants (P3, P8, P17) used Rescheduling to obtain more realistic plans when the initial schedule was not feasible.

Overall, participants found that the combination of these features helped them manage schedules that felt both actionable and acceptable. A notable appreciation was that P14: "*I think it might be hard to follow if the schedule were fixed. Giving me room to change really helped me follow through.*"

Perceived Appropriateness and Usability. Table 11 presents the survey results assessing the perceived appropriateness and helpfulness of EcoTailor. For usability, EcoTailor received a mean SUS score of 74.5 ($\sigma = 12.96$). The full list of SUS questions is available in Table 22 in Appendix A.9.

7.5.3 Responses to Proposed Schedules.

Responses to Transportation Suggestions. **EcoTailor encourages participants to choose more eco-friendly transport modes compared to their habits.** Figure 11 compares participants' average daily usage of each transportation mode between the Observation Period and the EcoTailor Period. Note that participants made an average of 8.4 trips per day during the Observation Period and 8.8 during the EcoTailor Period with no statistically significant difference ($p = 0.4$). As illustrated in the figure, the use of relatively low-carbon options such as walking, bicycles, and e-bikes increased, whereas the use of higher-emission modes, including e-scooters, buses, taxis, and cars, decreased during the EcoTailor Period.

Our interview findings suggest that this shift toward lower-carbon transportation occurred because EcoTailor helped participants perceive these options as realistic and actionable within their daily routines. P17: "*I took a bus as the schedule suggested. I used to drive that route, but I tried to follow the suggestion as I felt responsible, and it also seemed doable.*" Notably, P10: "*I always drove to Starbucks, taking 5-10 minutes. One day, [EcoTailor] suggested a schedule with a 25-minute walk to Starbucks. I had never considered walking there, but it seemed doable that day. Also, it's good for health and the environment! I just walked as suggested.*" Some participants (P2, P5, P17) found it difficult to change their routines on weekdays due to tight schedules. However, on weekends —with more flexibility— they were more likely to follow EcoTailor's suggestions and used public transportation.

Participants occasionally chose not to follow the suggested transport modes. Common reasons included (1) bad weather, (2) inconvenient public transport routes, and (3) the need to coordinate with others. P15: "*It's about 10 to 15 minutes by taxi, but the same trip by bus can take over an hour, including transfers. Public transportation in [City] isn't very good, so I don't usually take the bus if transfers are needed.*" P7: "*I usually travel with my labmates, so I can't always follow what [EcoTailor] suggests. But a few times, I asked if we could just walk together.*"

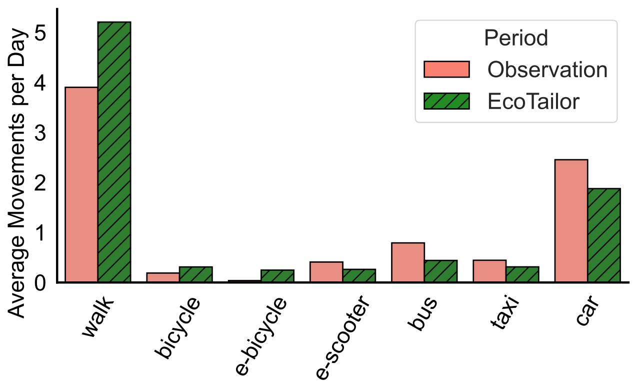


Fig. 11. Average daily movements by transport mode. Compared to the Observation Period, walk, bicycle, and e-bicycle increased during the EcoTailor Period, while the other modes declined.

Table 11. Questions assessing the perceived appropriateness of EcoTailor, rated on a 5-point Likert scale.

Question	μ (σ)
I found it difficult to use EcoTailor application.	2.61 (1.04)
I found it unable to follow the schedule generated by EcoTailor.	3.00 (1.03)
EcoTailor-suggested schedule helped me make informed choices.	4.11 (0.65)
Using EcoTailor helped me reduce carbon in daily life.	4.06 (0.64)
The study experience heightened my engagement with carbon-related issues.	4.33 (0.49)
This study inspired new actions I can take to reduce carbon in daily life.	4.06 (0.80)

Responses to Place Suggestions. **EcoTailor raises awareness of place-oriented carbon emissions but needs improvement to make suggestions more acceptable.** Participants had mixed responses to the system-suggested places, which were selected from category-compatible options. Some participants (P15, P17) found that EcoTailor-suggested places were appropriate for their activities. Even P5 and P11 attempted to follow the suggestions. In contrast, several participants (P1, P3–4, P6, P9, P13) chose not to follow the suggestions when they found them unappealing. This was mainly because the suggested places were roughly compatible rather than well-suited for the given event. P6: "*I've become aware (of the carbon emissions from places), but I sometimes use [another public space] when there's no room to do my task at [EcoTailor-suggested place].*"

Despite this, many participants reported becoming more conscious of the carbon emissions from their choice of place. P1: "*Through experiment, I realized that even doing the same thing can result in different carbon emissions depending on the place where I do that.*"

Perceived Autonomy over System Suggestions. **Participants retained autonomy in deciding whether to follow the schedule.** Participants did not unconditionally follow the schedules proposed by EcoTailor. The main reasons were: (1) the schedules were merely suggestions, and (2) unexpected situations sometimes made Rescheduling difficult or impractical. P15: "*It's just a suggestion, so it's up to me whether I follow it or not. It does make me think, 'Maybe I should try it,' but it doesn't feel like something I absolutely have to do.*" P5: "*When something unexpected came up or I had to leave in a hurry, I found myself using a car, despite my intention.*"

7.5.4 User Feedback on System Features.

Transportation Preferences. Participants called for more fine-grained control over the transport options provided by EcoTailor. Some (P5, P10) wanted to set different options depending on the nature of the upcoming event. For instance, they preferred to always drive to work but include bicycles or public transport for personal schedules. This reflects a need for flexibility that better aligns with situational habits and personal routines.

Carbon Feedback Representations. Participants also commented on carbon feedback. While some found numeric values effective (P5, P9, P11, P17–18), others preferred more tangible, metaphorical representations (P2–3, P6, P16). Several participants suggested relative indicators, such as comparisons to other users (P8–9) or their position within a broader population (e.g., "top X% of sustainable lifestyles"; P18). These responses suggest that carbon feedback should be both informative and personally meaningful.

Managing Input Burden. Several participants commented on the effort required to use EcoTailor over the two-week period. Entering activities and preferences involved manual input, which P2, P11, and P18 noted became faster and more routine as they grew familiar with the app. Still, P7 acknowledged that entry could feel burdensome on days with dense schedules. Relatedly, several participants (P10, P12, P15) suggested that EcoTailor would be more practical if integrated with existing calendar systems, such as Google Calendar or Apple Calendar, or if its core functions could be embedded directly into the tools they already use.

External Motivators for Sustained Use. Beyond the system's own feedback, several participants suggested factors that could sustain engagement. P15 expressed willingness to continue using EcoTailor, valuing the schedule tailoring itself as a feature not offered by other calendar applications. P10 noted that since many low-carbon schedules involve more walking, surfacing health benefits (e.g., calories) could motivate users.

8 DISCUSSION

As introduced in Section 1, this study set out to address these research questions: **RQ1.** How do people interact with tailored carbon-reduction schedules and what factors make the suggestions easier or harder to follow? **RQ2.** How do carbon emissions change when tailored schedules are provided? The Scenario-based in-lab study addressed both questions under controlled conditions through comparison with an awareness-raising baseline, while the In-the-wild Deployment revisited them through a four-week study in participants' actual lives.

The Scenario-based in-lab study examined EcoTailor under controlled conditions, comparing it against an Awareness-raising Condition at both the individual and persona levels. In the *Self-based Day Planning* task, participants using EcoTailor exhibited daily estimated carbon emissions significantly lower compared to those in the Awareness-raising Condition. Our analysis revealed how this result emerged in EcoTailor: beyond transport-mode substitutions, it enabled event-level reorganizations in time and place that proactively opened up more room to fit lower-carbon options. The *Persona-based Day Planning* task allowed us to indirectly probe how EcoTailor might operate across a wider range of demographic and situational contexts. EcoTailor exhibited significantly lower emissions for two of the three personas, but not for Persona A—the persona with the densest fixed commitments. This marks a natural boundary of tailored scheduling: event-level reorganization is one of the indigenous mechanisms of EcoTailor, while constrained when a day is already filled with fixed commitments.

The in-the-wild study then examined how EcoTailor functions in participants' actual daily lives. Participants' mean daily emissions were significantly lower during the EcoTailor Period than during their own Observation Period, with an average reduction of 5.48%. This effect is meaningful, but notably smaller than the 16.64% observed in the *Self-based Day Planning* task. A possible explanation can be found from the day-to-day trajectories (Figure 9 and 13), which illustrate the combined effect of the EcoTailor-suggested schedules under the interaction with real-life factors that vary daily. Unlike the in-lab condition in which participants assess a schedule's feasibility with respect to their typical routines, unexpected constraints or shifting priorities on some days might undermine their capacity or willingness compared to their typical days.

Together, the two studies suggest that the value of tailored scheduling lies not in maximizing reduction on any single day, but in expanding the lower-carbon options that remain realistic under varying daily conditions. While these results demonstrate promising potential, EcoTailor still leaves room for improvement. In the following sections, we discuss key considerations for embedding specific values—such as low-carbon practices—into everyday scheduling (Section 8.1), explore the broader implications of our actionability-based approach (Section 8.2), and outline limitations and directions for future work (Section 8.3).

8.1 Consideration for Integrating Values into Everyday Routines

Through the process of designing, implementing, and deploying EcoTailor, we identified several considerations for systems that aim to embed particular values into users' everyday routines.

Respect existing routines. Our findings highlight the importance of designing interventions that respect and align with users' existing patterns of action. Participants expressed lower satisfaction with place suggestions compared to transportation suggestions. We attribute this difference to how well each feature incorporated users' routines. For transportation, EcoTailor generated schedules within a set of user-defined options, thereby respecting one's constraints and habits. In contrast, place suggestions lacked such granularity, as preferences could vary even within the same category (e.g., cafe A vs. cafe B). To encourage acceptance, the system should build upon users' familiar places and routines—suggesting value-aligned alternatives that fit naturally within existing patterns. Moreover, accessibility and adoption could further improve if such value-oriented approaches are integrated into tools users already use, such as existing calendar applications, as mentioned in Section 7.5.4.

Preserve user autonomy. Planning plays a crucial role in expanding available options and creating new opportunities, inspiring the design of various systems that help with schedule generation—such as sleep planning [59], academic timetabling [70], medication schedules [49], and travel routing [12]. However, systems that proactively generate suggestions for users' daily decisions, including EcoTailor, may risk limiting autonomy by taking over responsibilities. Thus, it is important to carefully consider the appropriate level of intervention. Interestingly, our observations (Section 7.5.3) differed from this expected concern. While participants were aware of EcoTailor's suggestions, they often prioritized situational factors—such as physical condition, weather, or companions—when finalizing schedules. Upon unexpected events, they often created new schedules or ignored EcoTailor, rather than following its suggestions. These findings highlight the need for future systems that move beyond static suggestions, offering context-aware alternatives that remain actionable as users' situations change.

Reduce user burden. A core tension in EcoTailor's design lies between its information needs and the corresponding user burden. To generate schedules aligned with individual routines and momentary willingness, the system requires ongoing input about activities, preferences, and constraints. While our participants found this input effort generally manageable (Section 7.5.4), we acknowledge that they were supported by study compensation and regular check-ins, which may not generalize to voluntary, long-term adoption. For future systems that embed value-oriented scheduling into daily life, reducing this input burden is essential for sustained engagement. We see several directions for addressing this challenge. First, EcoTailor could leverage users' existing calendar data to automatically populate scheduled activities. Second, the system could learn from users' routines over time, inferring recurring activities and contextual states from daily, weekly, or longer-term patterns [21, 54, 60, 61] to reduce the need for repeated input. Third, the input modality itself could be redesigned for lower effort—for example, supporting natural language input or more customizable entry templates.

Address user well-being and privacy. The Willingness slider, while intended to support user autonomy, introduces considerations around well-being and privacy. Research on self-tracking systems suggests that persistent engagement with effort-related metrics can foster self-critical reflection rather than motivation [22, 23]. To mitigate the risk of discouragement, the system could reframe consistently low willingness as evidence of effort under constrained circumstances rather than a lack of engagement. It could further reinforce motivation by surfacing users' cumulative contributions over time, highlighting how small, incremental actions collectively amount to meaningful impact. Furthermore, aggregated willingness data over time may reveal patterns indicative of broader psychological states. Future deployments should also adopt a local-first storage model to ensure that such sensitive signals remain under the user's direct control.

8.2 Strategies to Increase Actionability in Broader Contexts

We see several opportunities to extend EcoTailor and enhance its actionability in broader contexts.

Enhancing individual preparedness. Within the current scope of EcoTailor, knowing when and where a person plans to visit could allow the system to provide more actionable, context-specific suggestions. For instance, if a user plans to visit a cafe, the system could remind them to bring a reusable tumbler before leaving home. Such timely and preparatory reminders could strengthen the practical enactment of sustainable intentions, bridging the gap between awareness and everyday action.

Scaling from individuals to shared contexts. EcoTailor performs scheduling based on a single user's calendar. However, as reported in Section 7.5.3, participants sometimes travel or carry out activities with companions. Companions influence the user's decisions as well as the joint carbon footprint of the activity, so accurately accounting for emissions requires considering them. This points to a shift from individual optimization to collaborative carbon-aware scheduling, where the unit of optimization is the shared activity rather than a single calendar. For social activities involving multiple parties, EcoTailor could minimize the joint emissions of all attendees—for example, by selecting a centrally accessible place, proposing times that align with low-carbon transit options for everyone, or opting for remote participation when aggregate travel costs outweigh the benefits of co-location. Such a system raises new design questions around preference elicitation across users, negotiation of competing constraints, and privacy-preserving sharing of place and mobility information.

Beyond the multi-user case, individual-level actions are also constrained by the surrounding infrastructure. Even highly motivated individuals face limits when public transportation or shared facilities do not align with sustainable practices—a pattern echoed by participants who avoided public transit when routes required multiple transfers. More broadly, an individual's carbon footprint is shaped by interdependencies that extend beyond personal choice—workplace norms around commuting and meeting formats, organizational policies on remote work, and the design of urban mobility systems. Tailored scheduling at the individual level can only act within the space these surrounding structures leave open. Future systems might engage with these structures in two ways. One direction is to extend EcoTailor toward space-aware scheduling, where coordinated actions among people who share places—such as workplaces, campuses, or buildings—could lead to larger collective effects. Another is to surface aggregate patterns from individual schedules to inform decisions at the organizational or municipal level, such as commuting policies or transit planning.

Expanding the scope of carbon sources. Within the goal of carbon reduction itself, personal footprints arise from many domains beyond what EcoTailor currently addresses. Electricity use at home, food choices, and waste generate smaller per-action emissions than transportation, yet their cumulative and habitual nature can produce meaningful ripple effects over time. Prior systems have addressed several of these domains at the moment of action, as discussed in Section 2.2. The scheduling perspective behind EcoTailor could complement these in-situ approaches by acting at a different layer: a wider time window opens room for arrangement—when to do laundry, cook, consolidate errands—so that lower-carbon options become reachable before the moment of decision arrives. Combining these two layers could expand the space of feasible carbon-aware action, but also raises new design challenges in how to present and negotiate trade-offs across heterogeneous behaviors.

Applying the approach to other domains. Beyond carbon-related scheduling, the design principles underlying EcoTailor could apply to domains that involve effortful, delayed-reward behaviors. For example, minor modifications to EcoTailor's scheduling algorithm could promote walking or healthy eating in daily routines. Like carbon reduction, these behaviors share a challenge: their outcomes are not immediately visible. Prior work has explored supporting such delayed-result behaviors [47, 51, 52, 77]. We believe that EcoTailor's approach—providing context-grounded and actionable schedules—could be effectively extended to these domains.

The role of technology in carbon reduction. Through the design and study of EcoTailor, we identified what technology can and cannot do in supporting low-carbon behavior. EcoTailor can lower the friction of lower-carbon options by surfacing them in advance and arranging the day around them. But translating these options into action ultimately depends on the user, shaped by factors largely outside the system—motivation, social context, and surrounding infrastructure. Designing for sustainability through technology, therefore, demands attention not only to what a system itself does, but also to how it interacts with surrounding conditions. This honest accounting also extends to technology's own carbon cost. Based on the server's power consumption, data-center overhead, and Korea's grid emission factor[2], we estimate that operating EcoTailor for our two-week deployment corresponds to approximately 7 gCO_2 per participant per day. Compared to the average daily carbon reduction per participant (321.4 gCO_2), this cost remains relatively small. At the same time, it still represents a source of emissions that sustainability-oriented systems should account for as part of their overall impact, especially as power-drawing technologies such as continuous sensing are introduced [71–73].

8.3 Limitations and Future Work

Limited demographic and deployment context. Our participants mainly consist of university students with a few full-time professionals. Since EcoTailor depends to some extent on users' flexibility, future work could consider a broader range of lifestyles, including those with tighter schedules or family responsibilities. Participants were modestly compensated. While such compensation is common and often mandatory for HCI studies, it may have influenced their level of engagement. Our deployment was conducted in a medium-sized city, where mobility infrastructure and environmental contexts may differ from those in metropolitan or rural regions. Future studies should test EcoTailor under more diverse infrastructural conditions.

Need for long-term investigation. Our four-week deployment offers an initial view of how EcoTailor fits into everyday routines, but cannot speak to whether its approach can foster sustained engagement over a month or longer. Future work could compare longitudinal usage patterns between EcoTailor and systems that suggest the most carbon-efficient options without considering users' current situations or intentions to better understand the relationship between adaptivity and long-term adherence.

Accuracy of carbon emission estimates. The carbon values presented in EcoTailor are statistical estimates and inevitably differ from actual emissions, as carbon accounting is approximate by nature [13, 34]. When approximations are presented as numbers, users may overestimate their reliability, even though the numbers may not reflect the actual emissions of a specific instance. While we made clear to participants that the values were statistical estimates, this is not a fundamental solution. One direction is to improve the accuracy of carbon estimation. We explored sensing-based approaches [46, 48, 55, 62]—detecting nearby Bluetooth devices to infer co-passengers, and implemented a prototype, but these signals proved unreliable in practice and could only confirm co-presence after the trip had begun—little helpful at the moment of planning. Achieving meaningful improvements would likely require advanced prediction of co-travel intents before a trip. An alternative is to support user judgment with informative framing: for example, indicating that a taxi shared by 3+ people approaches a bus-equivalent per-person footprint can help users reason about transport choices even when exact occupancy is unknown, and personalized or analogical framing may further support such reasoning [50]. Another question is how to communicate data of varying granularity to users. Possible approaches include providing explanatory statements alongside the data, differentiating visual representation depending on the granularity of estimates, and using interactive systems such as chatbots to correct users' misunderstandings [99].

Handling Uncertainty in Scheduling. Our algorithm uses deterministic travel-time estimates and does not model stochastic factors such as bus delays or missed connections, which can render a recommended schedule infeasible at execution time. Although rescheduling can partially recover from such disruptions, explicitly modeling uncertainty—through probabilistic travel-time distributions or built-in slack—remains future work.

Extensions for future studies. Our deployment tested EcoTailor as a single full-featured system, leaving room for extensions. First, ablation studies could isolate component-wise contribution to the system's overall effect. Second, while we compared EcoTailor with the Awareness-raising Condition in our in-lab study, our deployment did not include such a comparison. Future work could validate the deployment findings through between-subject designs in naturalistic settings, and could assess the Scheduler through heuristic measures such

[2]We assumed a server power draw derived from CPU TDP, RAM, and storage components, a Power Usage Effectiveness (PUE; the ratio of total facility energy to IT equipment energy) of 1.6 for the university server room, and a grid emission factor of 474.7 gCO_2/kWh [2].

as user satisfaction or comparisons against non-optimal schedules. Third, future research could investigate how combining different feedback modalities or established persuasive design strategies enhances user understanding and motivation.

9 CONCLUSION

We presented EcoTailor, an actionability-centered low-carbon daily planning system that helps each user balance sustainability with the realities of their everyday life. To ensure both practicality and environmental benefit, EcoTailor enables users to negotiate actionable daily schedules with feasible low-carbon choices that best fit their obligations and preferences. We identified user needs through a preliminary study, developed a working prototype, and conducted a controlled in-lab study and a four-week in-the-wild deployment. The findings demonstrated that EcoTailor provides actionable low-carbon options, leading to lower daily carbon emissions. We envision that this perspective can be extended to other domains—such as health, productivity, and well-being—where individuals continuously balance ideals with the realities of daily life.

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A APPENDIX

A.1 Carbon Emission details

Table 12. Per-person carbon emission for transportation (gCO_2/km/person) and places (gCO_2/hour/person), amortized by average ridership or occupancy.

Transportation	Carbon Emission	Place	Carbon Emission
walk	0	dormitory	115.21
bicycle	5	library	65.24
e-bicycle	25	lecture room	194.09
(shared) e-scooter	126.55	student hall	64.94
motorcycle	122.90	cafeteria	172.28
bus	51.25	gym	56.86
taxi	286.20		
car	258.75		

A.2 Survey Questionnaire in Preliminary Study

Types of Questions: (L) for Likert-scale, (S) for Single Response, (M) for Multiple Response, and (F) for Free-Form.

(1) How interested are you in carbon issues? (L)
  (a) What is the reason for answering like that? (F)
(2) To what extent are you committed to reducing carbon emissions? (L)
(3) Please select all the specific efforts you have been making in the past month. (M)
(4) What are the reasons for the effort/not effort? (M)
(5) Please select all the factors that you think are preventing you from making choices to reduce carbon (M).
(6) How much are you willing to invest in the following values for carbon reduction? [Time (e.g., using a bus or walking instead of taking a taxi)] (S).
(7) How much are you willing to invest in the following values for carbon reduction? [Money (e.g., using eco-friendly products even if they are more expensive)] (S).
(8) How much are you willing to invest in the following values for carbon reduction? [Effort (e.g., consciously saving water/electricity)] (S).
(9) What system(s) do you primarily use for schedule management? (M)
  (a) Why do you use (or not use) these methods? (F)
  (b) What are the limitations of your current method? (F)
(10) Would you be willing to use an application that plans your daily life or travel like the one described above? (L)
  (a) What is the reason for answering like that? (F)
(11) Would you be willing to use an application that goes beyond the one mentioned above and creates a more personalized schedule by considering your values (cost, time required, and environmental impact)? (L)
(12) Based on the given information (7 different cases in Table 13 in Appendix A.2, which mode of transportation would you choose? (S)
(13) What was the most important value you considered when answering above questions? (S)
(14) If your choice of transportation changed or did not change, what was the reason? (F)
(15) What are the reasons for choosing a different mode of transportation than usual? (F)
(16) Please select all the activities you have carried out at (home/workspace/classroom/library/cafe/park/indoor workout facilities/outdoor workout facilities/religious institutions) in the past month. (M)

(17) Please describe the places you have frequently used in the past month and the activities you performed at those places that were not mentioned above. (F)
(18) Do you generally follow a fixed routine in terms of places? (L)
(19) How many places do you use more than three times a week, and approximately how many people use each of those places with you? (F)
(20) Please select all the criteria you use when choosing a place to carry out your tasks. (M)
(21) If your primary place for daily activities has a high carbon emission, would you be willing to switch to a more eco-friendly alternative? (L)
   (a) Why did you choose this answer? (F)
(22) Please select all the reasons why you used (walking/bicycle/electric scooter/electric bicycle/subway/taxi/bus/car/train/airplane) as a mode of transportation in the past month. (M)
(23) Please select up to four transport modes that you use most frequently on average from the ones mentioned above. (M)
(24) What is the most important factor when choosing a mode of transportation? (S)

Table 13. Sets of different cost information for transportation, selectively shown per question in Survey Part-3. The participant was asked Q3.1 : "Which means of transport would you choose to go to the restaurant?" without any information. Q3.2 asks the same question but under a 'short duration' condition, where the travel times are specified as 24 minutes for walking, 17 minutes for the bus, and 5 minutes for a taxi. Similarly, Q3.3 repeats the question under a 'long duration' condition, where the travel times increase to 60, 28, and 10 minutes, respectively. From Q3.4 to Q3.7, participants are selectively provided information about transportation fare, calorie expenditure, or carbon footprint, which are presented as abstract emojis or detailed gram values. (O: shown; -: not shown).

Condition		**Transport cost**			**Question**						
		Walk	**Bus**	**Taxi**	**Q3.1**	**Q3.2**	**Q3.3**	**Q3.4**	**Q3.5**	**Q3.6**	**Q3.7**
Duration	Short (min)	24	17	5	-	O	-	-	-	-	-
	Long (min)	60	28	10	-	-	O	O	O	O	O
Expense (USD)		0	1.06	4.0	-	-	-	O	-	-	-
Exercise effect (kcal)		180	60	0	-	-	-	-	O	-	-
Carbon	Abstract	3 leaves	1 leaf	X icon	-	-	-	-	-	O	-
	Detailed (g)	0	173	732	-	-	-	-	-	-	O

A.3 Transportation Modes Reported in Individual Interview

Table 14. Transportation modes reported by interview participants. Conditional choices appear in parentheses.

P	Primary Modes	Conditional Choices	P	Primary Modes	Conditional Choices
P1	Walking, bus, bike	Taxi (long distance)	P10	Bike, bus	Walking (weather permitting)
P2	Walking, bus, taxi	Taxi (in a rush), bus (less crowded), walking (cooler weather)	P11	Walking, bike	Taxi (crowded)
P3	Walking, bus	—	P12	Walking, bus	—
P4	Walking, bus	—	P13	Walking, bus, subway, taxi	—
P5	Walking, subway, bus	—	P14	Walking, bus	—
P6	Walking, bike, personal car	—	P15	Walking, bus, subway	—
P7	Walking, bus	—	P16	Walking, bus, e-scooter	—
P8	Walking, bus	—	P17	Walking, subway, bike, e-scooter	Taxi (very long distance)
P9	Walking, bus, e-scooter	Taxi (crowded)	P18	Walking, bus, bike	—

A.4 Codebook from Formative Interview Thematic Analysis

Table 15. Representative codes from the formative interview analysis ($N = 18$), grouped by theme and sub-theme.

Sub-theme	Representative codes
Theme 1: Feasibility of a plan is personal, contextual, and shifting	
1.1 Feasibility depends on temporal arrangement	Order-constrained feasibility, Arrangement over mode, Post-task buffer, Pre-meal exercise avoidance, Post-meal walk
1.2 Feasibility depends on personal preferences and constraints	Variable walking tolerance, Residence-bound modes, Place-bound activities, Place-flexible activities, Home-only activities
1.3 Feasibility shifts with daily states	Weather-induced mode shift, Fatigue-induced mode shift, Companionship-induced mode shift, Time-pressure-induced mode shift
Theme 2: Acceptance of system-suggested schedules requires feasibility, not just low carbon	
2.1 Carbon-minimizing schedules are rarely top-ranked	Feasibility over carbon, Walking-distance rejection, Time-slot rejection
2.2 Acceptance fluctuates with daily state and information framing	State-conditional acceptance, Quantified-info reconsideration, Carbon as tiebreaker, Weather-conditional acceptance, Daily-capacity acceptance
Theme 3: Users wanted assistance that leaves the final choice to them	
3.1 Users welcome assistance that leaves final authority with them	Planning help welcomed, Delegation acceptable, Fixed-plan resistance, Recommendation over prescription, Autonomy preservation
3.2 Users wanted impact framed in terms they value	Multi-dimensional trade-off reasoning, Cost framing, Health framing, Quantitative impact feedback
3.3 System contributions must be visually distinguishable	System-vs-user distinction, Category-based color coding, Eco-element highlighting

A.5 Preferences Details

Table 16. Preferences details.

Preference Type	Detail	Options
Time of the day	focused	morning, afternoon, night, dawn
	exercise	before the day starts, morning, afternoon, after the day ends
Transport modes	available transportation	bus, bicycle, e-bicycle, e-scooter, motorcycle, car, taxi
	single walk	15, 20, 25, 30, 35, 40 minutes, more than 40 minutes
	cumulative walk	30, 40, 50, 60, 70, 80, 180 minutes, more than 180 minutes

A.6 Example Schedules from the EcoTailor Scheduler

To illustrate how the EcoTailor Scheduler behaves, we compare its output against a greedy baseline that minimizes total carbon emissions while completing the day's required events. Because a carbon-minimizing objective does not account for user preferences, the schedule it produces can often conflict with what a user is willing to do. We illustrate this with Maya's scenario from the Introduction.

Maya's profile and today's tasks (Table 17) are as follows:

- She prefers walking and public transit over driving.
- She is comfortable walking up to 30 minutes at a stretch, but under unfavorable conditions such as heat or fatigue, she may not be willing to walk that much.
- She prefers to do her personal exercise only after the day's tasks are done.

Table 17. Maya's fixed (left) and flexible (right) tasks for the day.

Time	Activity	Location	Activity	Duration	Constraint
10:00–11:00	Seminar	Home	Focused work	2 hr	flexible location
15:00–15:40	Dentist	Downtown	Pho lunch	45 min	fixed location; around 11:30–14:00
			Personal exercise	30 min	preferably after the day's tasks

As Figure 12 shows, the schedule generated by a greedy baseline minimizes Maya's emissions to about 696 gCO_2. But is such a schedule acceptable to her? Following it would require her to walk beyond her comfort on two of her trips—45 and 60 minutes, exceeding even her usual 30-minute preference—and to do her exercise in the morning, rather than after her day's tasks as she prefers. In contrast, EcoTailor offers a range of candidates that all respect Maya's preferences. At maximum willingness (Willingness 5), its schedule keeps every walk within her 30-minute limit and places exercises after her day's tasks, emitting about 981 gCO_2. This is higher than the greedy version, but the increase comes almost entirely from replacing her long walks with short e-bicycle trips. On a pleasant day Maya might well adopt this schedule. But when she starts her day feeling hot or tired—conditions under which she may not be willing to walk as much as 30 minutes at a time—she can step down to a lower-willingness option, trading some carbon savings for shorter walks and greater comfort. Rather than committing to a single carbon-optimal plan, EcoTailor spans a range of schedules that let Maya choose the point that fits her willingness on a given day.

Fig. 12. Three schedules for Maya's day. The carbon-minimal (greedy) schedule reaches the lowest emissions but violates Maya's preferences (red), while EcoTailor's candidates (Willingness 5, Willingness 3) respect them at a modest increase in emissions.

A.7 Schedule Generation Pipeline

EcoTailor's schedule generation pipeline (Pipeline 1) proceeds in two stages. In Stage 1, we encode the scheduling problem as a Mixed-Integer Linear Program (MILP), where binary decision variables represent (i) the time slot assigned to each flexible event e_k^{flexible} within available gaps between fixed events and (ii) the transport mode $t \in \mathbb{T}_{\text{pref}}$ for each gap. The constraints in Eq. (1)–Eq. (2)—including place rule, gap capacity, and transit feasibility—are expressed as linear inequalities. In Stage 2, we solve the MILP for each willingness level $\lambda_i \in \Lambda$ using the λ_i-weighted objective in Eq. (3). The values in Λ are ordered so that smaller λ prioritize travel time (user convenience) and larger values prioritize carbon reduction, reflecting different willingness levels. We use HiGHS [45] as the solver.

Pipeline 1: EcoTailor candidate schedule generation via MILP

Input: $\mathbb{E}_{\text{fixed}}, \mathbb{E}_{\text{flexible}}, \mathbb{P}_{\text{option}}, \mathbb{T}_{\text{pref}}, \Lambda = \{\lambda_1, \ldots, \lambda_5\}$ (ascending)
Output: Candidate schedules $\mathcal{S} = \{S_1, \ldots, S_5\}$

```
// Stage 1: Encode inputs as an MILP
```

Discretize the day into fixed-length time slots and identify gaps between consecutive fixed events
Define an MILP $\mathcal{M}$ with binary decision variables for:
(i) the slot assigned to each e_k^{flexible} within a gap,
(ii) the transport mode $t \in \mathbb{T}_{\text{pref}}$ chosen for each gap,
encoding the constraints in Eq. (1)–Eq. (2): place rule, gap capacity, transit feasibility

```
// Stage 2: Solve under each willingness level
```

$\mathcal{S} \leftarrow \emptyset$
foreach $\lambda_i \in \Lambda$ **do**
  $S_i \leftarrow$ Solve($\mathcal{M}$) under the λ_i-weighted objective (Eq. (3)) using HiGHS
  $\mathcal{S} \leftarrow \mathcal{S} \cup \{S_i\}$
return $\mathcal{S}$

A.8 Quantitative Analysis Results from the Scenario-based In-lab Study

Table 18. Behavioral intention (BI) and behavioral expectation (BE) scores by scheduling task and condition. Scores are on a 7-point Likert scale. p-values are from Mann–Whitney U tests.

Scheduling Task	Measure	Awareness-raising Condition M (SD)	EcoTailor Condition M (SD)	p
Self-Based	BI	6.26 (0.87)	6.00 (0.82)	.26
	BE	5.74 (0.81)	4.84 (1.61)	.14
Persona A	BI	6.05 (0.85)	6.00 (0.75)	.78
	BE	5.68 (1.29)	5.58 (1.17)	.72
Persona B	BI	6.26 (0.81)	5.95 (0.97)	.26
	BE	5.68 (1.00)	5.79 (1.32)	.55
Persona C	BI	6.11 (1.10)	6.05 (0.62)	.36
	BE	5.58 (1.26)	5.79 (0.85)	.70

Table 19. Task completion time (in minutes) by scheduling task and condition. p-values are from Mann–Whitney U tests.

Scheduling Task	**Awareness-raising Condition** M (SD)	**EcoTailor Condition** M (SD)	p
Self-Based	9.75 (3.53)	4.52 (1.95)	<.001
Persona A	7.88 (2.64)	4.04 (1.61)	<.001
Persona B	7.44 (1.49)	4.00 (1.64)	<.001
Persona C	9.18 (2.33)	5.15 (1.86)	<.001

Table 20. Hedonic TAM scores by condition. Scores are on a 7-point Likert scale. p-values are from Mann–Whitney U tests.

Dimension	**Awareness-raising Condition** M (SD)	**EcoTailor Condition** M (SD)	p
Perceived Usefulness (PU)	5.12 (1.38)	5.24 (1.19)	.80
Perceived Ease of Use (PEOU)	4.70 (1.48)	4.96 (1.08)	.79
Intention to Use (ITU)	4.44 (1.85)	4.37 (1.43)	.84
Perceived Enjoyment (PE)	4.91 (1.42)	4.72 (1.26)	.65

Table 21. Persona perception ratings by condition, on a 7-point Likert scale (N = 19 per condition). Values are reported as $M(SD)$ and Mdn.

Category	**Item**	**Persona**	**Awareness-raising Condition**		**EcoTailor**	
			$M(SD)$	Mdn	$M(SD)$	Mdn
Manipulation check	Schedule flexibility perceived	A	2.47 (1.26)	2	2.26 (1.28)	2
		B	5.42 (1.22)	6	5.32 (1.16)	5
		C	6.05 (1.35)	7	6.47 (0.61)	7
Clarity	Information was easy to understand	A	6.00 (1.20)	6	6.26 (0.65)	6
		B	5.84 (1.30)	6	6.53 (0.61)	7
		C	5.89 (1.37)	6	6.68 (0.48)	7
	Persona’s situation was clearly conveyed	A	6.16 (1.17)	6	6.47 (0.61)	7
		B	6.11 (1.52)	7	6.53 (0.77)	7
		C	6.00 (1.25)	6	6.58 (0.61)	7
Credibility	Persona felt like a real person	A	6.63 (0.50)	7	6.68 (0.75)	7
		B	5.11 (1.70)	5	6.05 (1.22)	6
		C	5.37 (1.95)	6	6.37 (0.96)	7
	Persona’s situation felt realistic	A	6.26 (0.93)	7	6.53 (0.84)	7
		B	5.21 (1.78)	6	5.79 (1.40)	6
		C	5.47 (1.65)	6	6.42 (1.02)	7
Empathy	Could fully understand the situation	A	6.47 (0.84)	7	6.58 (0.61)	7
		B	5.58 (1.71)	6	6.32 (0.67)	6
		C	5.74 (1.37)	6	6.58 (0.69)	7
	Tried to think from persona’s perspective	A	6.68 (0.48)	7	6.68 (0.58)	7
		B	6.47 (0.77)	7	6.63 (0.68)	7
		C	6.53 (0.61)	7	6.68 (0.48)	7
	Could imagine a day as this persona	A	6.47 (1.17)	7	6.53 (0.84)	7
		B	6.00 (1.45)	6	6.53 (0.51)	7
		C	6.16 (1.46)	7	6.32 (0.75)	6

A.9 System Usability Scale Question

Table 22. System Usability Scale (SUS) questions.

Number	Question
#1	I think that I would like to use EcoTailor system frequently.
#2	I found that EcoTailor system unnecessarily complex.
#3	I thought EcoTailor system was easy to use.
#4	I think that I would need the support of a technical person to be able to use EcoTailor system.
#5	I found the various functions in EcoTailor system were well integrated.
#6	I thought there was too much inconsistency in EcoTailor system.
#7	I would imagine that most people would learn to use EcoTailor system very quickly.
#8	I found EcoTailor system were very cumbersome to use.
#9	I felt very confident using EcoTailor system.
#10	I needed to learn a lot of things before I could get going with EcoTailor system.

A.10 Quantitative Analysis Results from the Deployment Study

Table 23. Summary of Pre- and Post-Survey Results for Items Assessing Perceptions of Climate Change and Carbon Issues.

Question	pre mean	post mean	p-value
Global warming refers to the idea that the world's average temperature has been increasing over the past 150 years, may be increasing more in the future, and that the world's climate may change as a result. Do you think that global warming is happening?	3.000	3.000	1.00
Even if you don't know, what's your best guess about whether global warming is happening?	3.000	3.000	1.00
How sure are you that global warming is happening?	6.444	6.278	1.00
Have you personally experienced the effects of global warming?	5.556	5.833	1.00
How much do you think carbon emissions contribute to global warming?	6.000	6.000	1.00
How much do you think global warming will harm you personally?	5.444	5.722	1.00
How much do you think global warming will harm society?	6.333	6.556	1.00
How worried are you about carbon emissions?	4.333	5.222	0.33
How much had you thought about global warming and carbon emissions before today?	2.944	3.333	0.66
How important is the issue of global warming to you personally?	5.333	5.833	1.00
How important is reducing carbon emissions to you personally?	4.944	5.444	1.00
How much personal responsibility do you feel to help reduce global warming and carbon emissions?	4.667	5.778	0.07
How much do you agree that an individual's actions cannot make any difference in reducing carbon emissions?	3.389	1.889	0.02^{*}
How much do you agree that new technologies can solve global warming without individuals having to make big changes in their lives?	4.611	3.778	0.21
How much risk do you think extreme weather events caused by global warming and carbon emissions will pose to your community over the next 10 years?	6.056	6.222	1.00
How much do you think individuals should make an effort to solve the carbon problem?	5.556	5.722	1.00
How much do you think society should make an effort to solve the carbon problem?	6.667	6.722	1.00
How much do you support a policy to build more bicycle lanes?	5.722	5.667	1.00
How much do you support a policy to increase public transportation use by improving or adding routes?	6.278	6.222	1.00

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$. Bonferroni-adjusted p-values are reported.

A.11 Per-Participant Daily Carbon Trajectories During Deployment

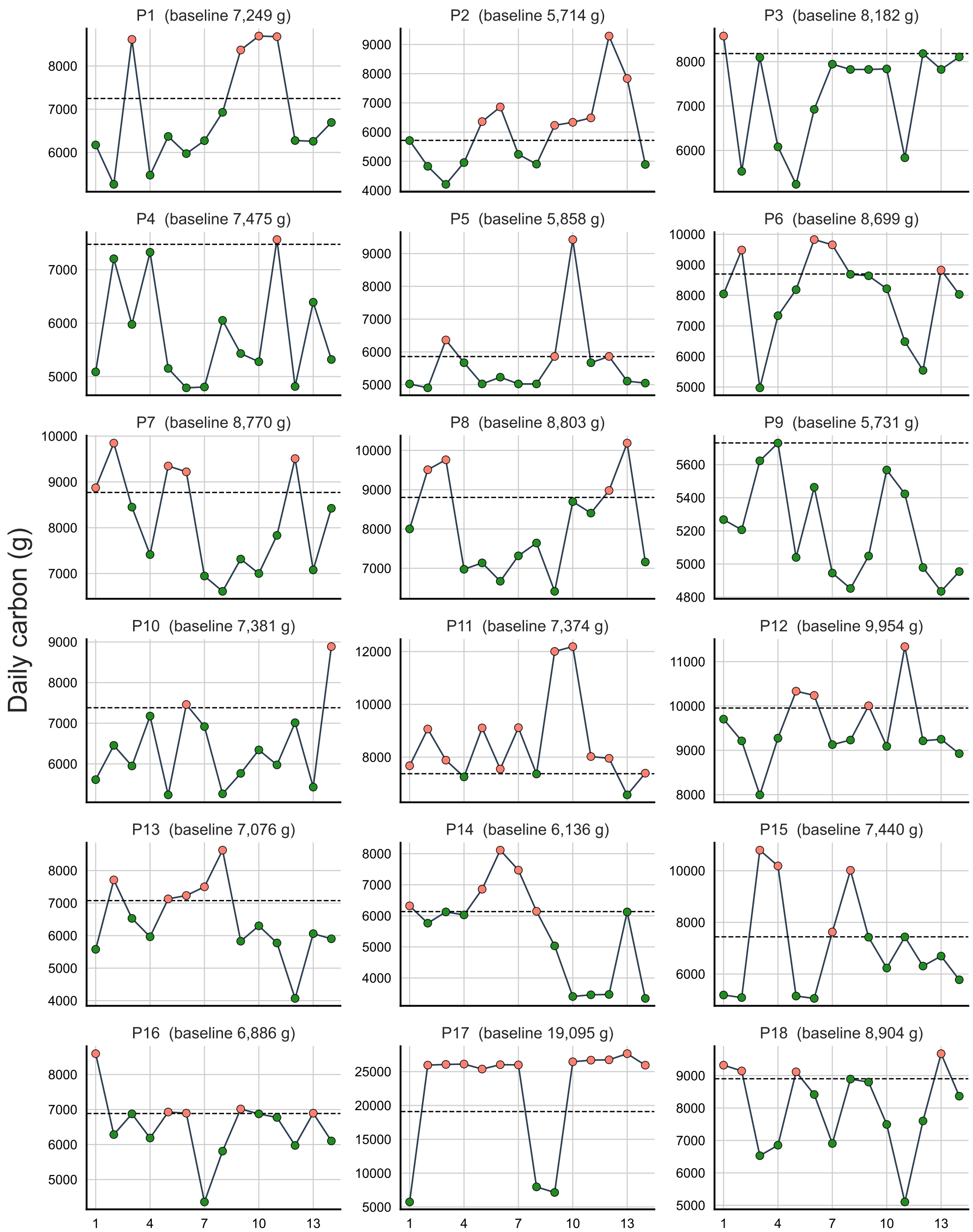

Fig. 13. Per-participant daily carbon trajectories during the EcoTailor Period. Each panel plots one participant's daily carbon emissions (g) throughout deployment, with the dashed horizontal line marking that participant's Observation Period mean as a personal baseline (annotated in each title). The figure illustrates the magnitude and pattern of day-to-day fluctuations relative to each individual's pre-intervention baseline.