

Visualizing and “Budgeting” the Emissions of Everyday GenAI Use

Yuheng Ren , Luiz Augusto Morais, Frédérique Krupa, Francisco Paulo Magalhães Simões, Nivan Ferreira and Georgia Panagiotidou

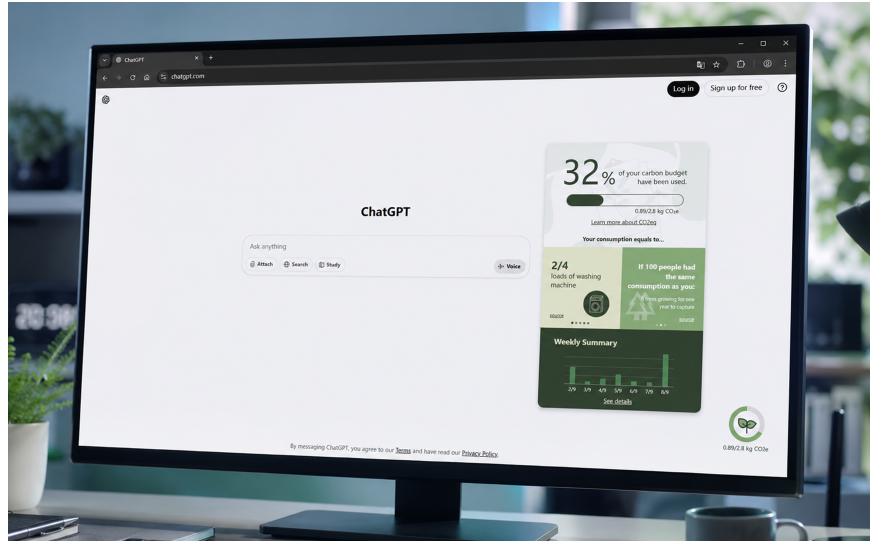


Fig. 1: EcoChat displays visualized information on carbon emissions and carbon budgets through the icon and pop-up at the bottom right corner of the ChatGPT interface.

Abstract—While the environmental impact of GenAI becomes increasingly significant, and a growing number of tools that aim to raise awareness of this issue, limited attention has been paid to how such information should be visualized and communicated to end users, especially in ways that are easy to understand and interpret. To this end, we designed EcoChat, a Chrome browser extension for the web-based ChatGPT that visualizes carbon emissions of its usage in real time. EcoChat uses various metaphorical representations to contextualize the carbon emissions data and enables users to set up “carbon budgets”, which are carbon emission allowances representing their own personal goals. Users can compare their carbon budgets with their actual emissions to foster environmental awareness. We reflect on EcoChat’s design choices in the context of the current landscape of AI eco-feedback tools, discussing how it addresses several identified shortcomings while also highlighting remaining challenges and future research directions.

Index Terms—Environmental Impact of AI, Generative AI, Environmental Awareness, AI Inference

1 INTRODUCTION

Generative AI (GenAI) has become increasingly integrated into people’s work and everyday lives. Tools such as ChatGPT handle millions of queries daily [40], reshaping how people accomplish their professional and personal activities and boosting their productivity [16,32,41]. However, its widespread use has also brought about significant environmental costs [4,9,10]. The training and deployment of these GenAI models rely on data centers, which can consume large amounts of energy, including electricity [23] and water [28], and consequently generate a substantial carbon footprint [19].

Despite these significant environmental costs, end users, who frequently engage with GenAI tools, have little visibility into their environmental consequences. Tools exist to communicate the environmental

impact of GenAI [3,6,8,12,26] have largely focused on the training phase of GenAI models and targeted developers as their primary users. As a result, end users have been largely excluded from this discourse, yet making these consequences visible to them is worthwhile. Beyond potentially fostering more resource-conscious usage habits through the traditional “awareness-to-behaviour-change” pathway [25], access to such environmental information is a fundamental aspect of users’ right to understand the broader consequences of the technologies they use [13,15]. It gives them the agency to make informed decisions about their GenAI usage [29] and to engage in debates over the future sustainable development of GenAI [22].

While recent efforts have begun to shift attention toward measuring the environmental cost of inference and providing tools directly to end users [17,37], limited attention has been paid to how such information should be designed and communicated to end users. Therefore, we designed EcoChat, a Chrome extension that quantifies and visualizes the carbon footprint of ChatGPT usage. EcoChat is implemented as a browser extension specifically tailored to the web-based ChatGPT interface, ensuring easy user access to emissions data. It presents both numerical values and metaphorical representations of individual and collective carbon emissions, providing an anchor for magnitude judgments and making emissions data relatable. Notably, EcoChat allows users to set up a personalized “carbon budget”, a predefined carbon emission allowance over a specified timeframe, to relate environmental

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impact to their own goals, prompt self-reflection on the carbon footprint of their own GenAI usage, and foster greater environmental awareness. We deployed EcoChat in an in-the-wild study with 52 participants and reported the deployment findings in past work [36]. This paper focuses on the design process of EcoChat and reflects on these (visualization) design decisions to inform potential future work.

2 BACKGROUND AND RELATED WORK

As global energy-related carbon emissions continue to rise [21], electricity demand from AI-driven data centers is projected to double by 2026 [20] and account for 9.1% to 11.7% of total U.S. electricity demand by 2030 [39]. For the inference phase, i.e., the steps taken to generate a response from the user query on a previously trained model [42], a GPT-4o prompt is estimated to require 0.047 Wh, whereas generating an image consumes 60 times more energy, around 2.9 Wh [29]. Google reported 0.24 Wh for the median Gemini Apps text prompt and Mistral estimated 1.14 g CO_{2eq} per 400-token Le Chat response [2, 11]. These numbers, which seem small on the outset, can quickly add up in real-world usage scenarios [23, 29].

Due to a lack of transparency from GenAI tools providers about where models are trained and how much energy is used, getting precise metrics or comparing environmental footprints has long been difficult [30]. Nonetheless, as one way of responding to these environmental challenges, a range of tools have been developed to estimate GenAI’s energy consumption and carbon emissions [3, 6, 8, 12, 26]. Their estimates typically rely on hardware and workload metrics (e.g., GPU, memory, and runtime) together with estimation formulas. Existing tools also tend to rely on relatively simplistic design to communicate GenAI’s environmental impact information and aim to promote pro-environmental behavioral change. Consequently, the information remains disconnected from users’ everyday frames of reference and is largely presented as passive metrics, limiting users’ ability to meaningfully interpret the data and make informed decisions about their GenAI use [18]. Overall, there remains limited consideration of how to communicate the environmental impacts of GenAI inference in ways that make the information accessible, comprehensible, and actionable for end users.

3 EcoCHAT

We designed and implemented EcoChat as an extension for the Chrome browser that provides information on the carbon footprint of users’ ChatGPT usage (see Figure 1). This section outlines the design process and final implementation of EcoChat.

3.1 Design Process

EcoChat’s concept emerged through an iterative design process combining literature review, brainstorming, sketching, and internal critique across multiple cycles (see Figure 2). Rather than treating early design decisions as fixed, we revisited and tested each choice against principles and evidence drawn from prior work, refining earlier decisions as new insights surfaced over the course of the process.

3.1.1 Brainstorming Sessions

To identify the key features required for our system, we first reviewed related work on existing tools for communicating the environmental impact of GenAI, energy and carbon feedback systems in other contexts (e.g., homes and workplaces), and design examples related to environmental sustainability, and conducted several rounds of brainstorming and sketching. The review and design activities were carried out in parallel over one month, and we identified carbon emissions as the primary metric, as they are widely adopted, relatively familiar to the general public, and supported by mature estimation methodologies [37]. Additionally, during brainstorming sessions, we explored several traffic-light style interface designs (green/yellow/red) as an initial design direction for communicating emissions levels, leveraging their familiarity and immediate legibility (see Figure 2(A)).

Following the initial brainstorming session, we conducted an internal design review to evaluate the resulting concepts, in which the design direction was challenged: prior work has cautioned that such

evaluative color-coded schemes carry strong normative connotations by explicitly framing user behavior as “good” or “bad” [24, 38], nudging users toward a predetermined “correct” behavior rather than supporting informed decision-making [5]. Therefore, we established a guiding design principle: feedback should support users’ own reflection and judgment rather than direct their behavior, and conducted the second brainstorming session.

Guided by our design principle, we explored different approaches to representing carbon emissions in the second brainstorming session. However, we repeatedly encountered a tension between providing contextual references to support users’ understanding and introducing evaluative judgments about their environmental impact. To address this tension, we decided that the reference point should be defined by users themselves rather than externally imposed. This led us to introduce the “carbon budget” feature. By framing carbon emissions as a limited resource that can be monitored and managed over time, this feature enables users to compare their expected and actual emissions as well as supporting self-reflection.

The second brainstorming period lasted around two weeks, during which we developed several representations of the carbon budget feature (see Figure 2(B)). In the subsequent review session, we identified the limitation of relying solely on carbon budgets to help users understand their emissions levels: users may lack the necessary knowledge to meaningfully interpret these values. Therefore, we established another design principle: carbon emission figures should be made more relatable and easier to interpret. Guided by this principle, we further introduced metaphorical representations of carbon emissions. Metaphors can reduce the cognitive effort required to interpret abstract concepts by mapping them onto familiar and concrete source domains, and thus have become a common strategy in scientific and data communication [35], particularly for visualizing energy use and carbon emissions, which are abstract and largely imperceptible in everyday experience [14].

Following this, we conducted the third brainstorming session to identify effective metaphors and explore how they could be integrated into the interface (see Figure 2(C)). We surveyed related work to identify metaphors commonly used in the energy and environmental domains, then explored how they could be visually represented and integrated with the existing carbon budget feature. The third brainstorming period lasted another two weeks, and during the discussion, we developed two criteria for screening candidate metaphors: first, metaphors should be grounded in everyday, familiar experiences, to try to make them intuitive and interpretable. Second, they should be emotionally neutral to avoid evoking anxiety, guilt, or a sense of hopelessness, which can lead to passive engagement [31]. In the end, we arrived at the final set of metaphors used in EcoChat, including washing machine usage, electric scooter mileage, stove operation duration, email transmissions, and phone charging cycles.

3.1.2 Prototyping & Implementation

Through discussions during this iterative design process, we further incorporated additional features into the interface, including historical data and collective information. Historical data visualizes users’ self-generated emissions trends over time, drawing on prior work on personal information reflection [1, 27]. We also introduced a collective perspective, inspired by prior research in non-AI contexts showing that situating individual behavior within a broader social context can increase engagement and perceived relevance [7, 33, 34]. Although we initially considered presenting average emissions across users (see Figure 2(D)), we found that this approach conflicted with our guiding principle by reintroducing evaluative framing and potentially triggering boomerang effects, where low-impact users increase their usage toward a perceived norm [38]. Instead, we represented collective impact metaphorically by showing the emissions generated if one hundred people shared the user’s usage pattern, alongside familiar equivalents, including trees required for carbon absorption, flight distances and CO₂ fire extinguisher usage. These representations help users intuitively understand the cumulative significance of their individual footprint while addressing the perception that individual actions are too small to make a difference.

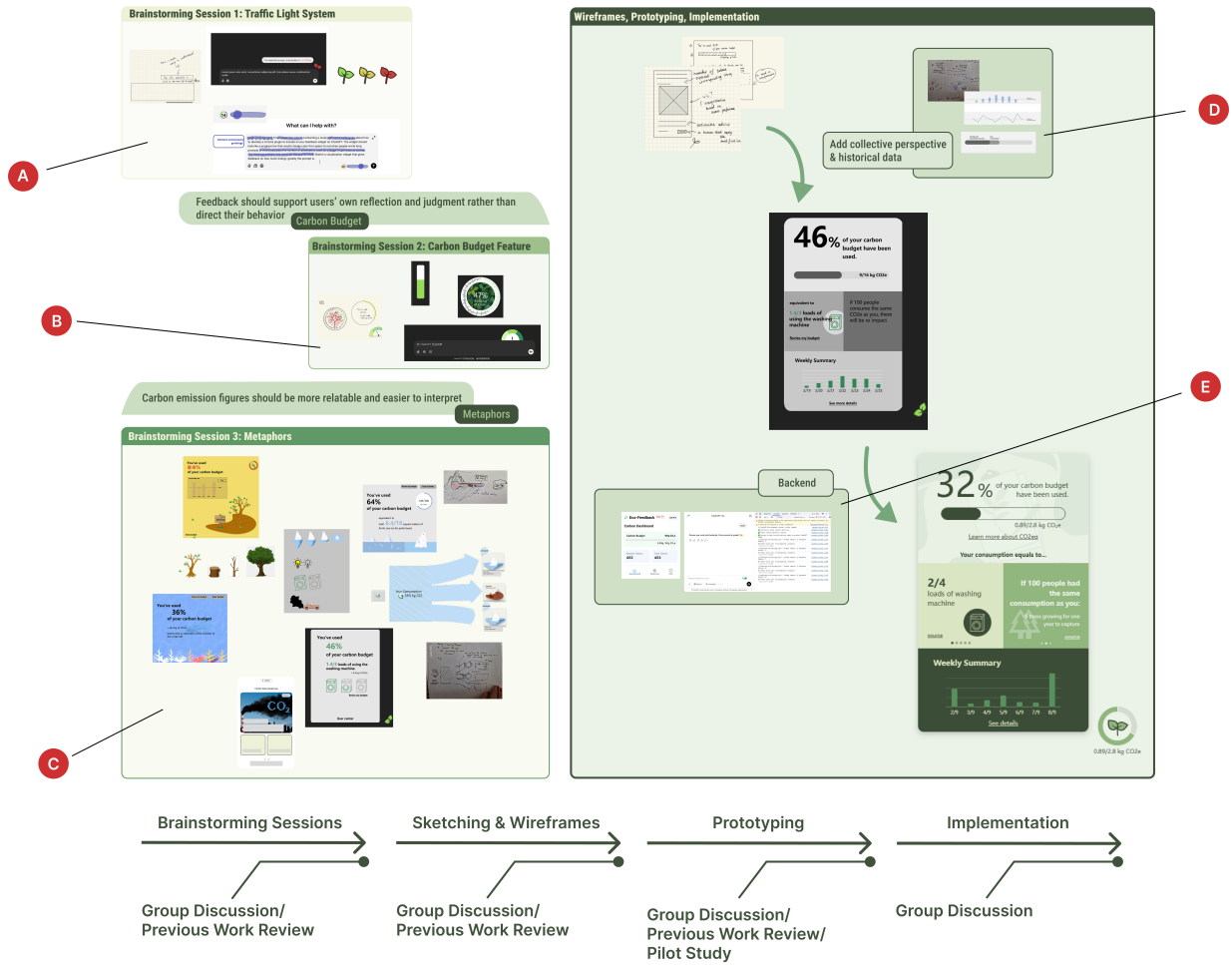


Fig. 2: **Overview of EcoChat's iterative design process.** (A) Physical and digital sketches from the first brainstorming session exploring the traffic-light system, using colored leaf or circular icons to imply the emissions level. (B) Sketches from the second brainstorming session exploring interface representations of the carbon budget feature, including a circular percentage gauge, ambient and battery-style progress indicators. (C) Sketches from the third brainstorming Session exploring candidate metaphors for representing carbon emissions. Metaphors such as polar bear, melting ice, and coral reef were excluded in the final interface according to our criteria. (D) Sketches incorporating collective perspective and historical data into the interface. (E) Basic front-end and backend implementation, later refined through iteration into the final interface.

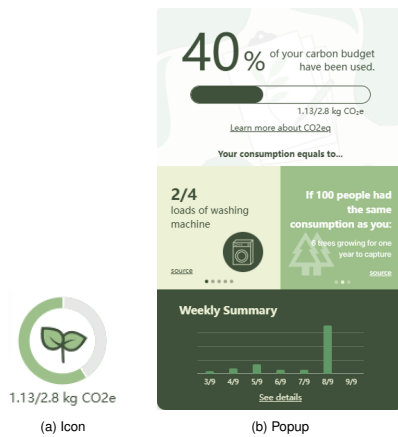


Fig. 3: **EcoChat Interfaces.** (a) The icon features a leaf motif encircled by a progress ring: the gray segment represents the consumed portion, and the green indicates the remaining budget, with CO₂eq value shown below. (b) The popup offers more detailed carbon footprint information.

3.2 Working Principles

EcoChat was implemented as a React-based browser extension with a Supabase backend. During ChatGPT interactions, it locally monitors prompt and response token counts using *js-tiktoken*, estimates carbon emissions based on the EcoLogits methodology¹, and updates emission indicators in real time. EcoChat's emission estimates represent a conservative lower bound, whose accuracy is limited by undisclosed model specifications and the use of a global rather than location-specific electricity mix. To preserve user privacy, only input and output numerical token counts are transmitted to the backend, while all conversational content is neither stored nor uploaded.

3.3 Final Interface and Interaction Design

Upon initial launch, EcoChat displays a welcome page at the center of the screen (see Figure 4). Users can adjust their language preferences² or click “start” button and log in. After logging in, users are introduced to the concept of carbon budget and proceed to a setup page where they define a personalized budget. This budget is specified through emission equivalents of five everyday activities and objects, with user-specified

¹https://ecologits.ai/latest/methodology/llm_inference (June 2025)

²EcoChat was deployed in English, Brazilian Portuguese and French.

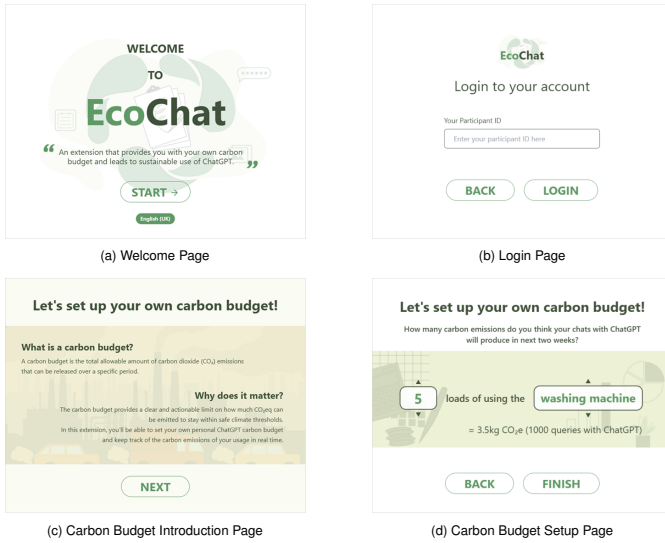


Fig. 4: Welcome Pages Display.

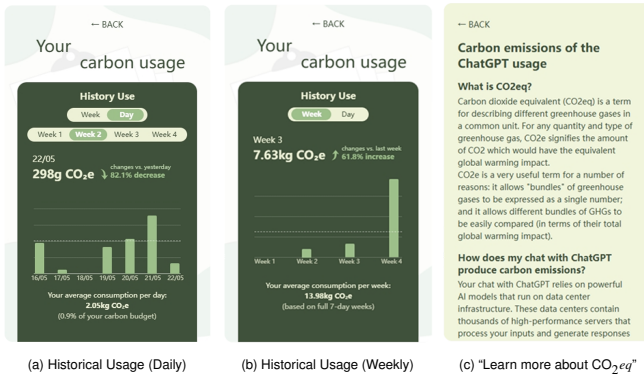


Fig. 5: Historical Data and Additional Information Pages Display.

quantities being converted into the number of ChatGPT queries and a customized budget.

After initialization or during usage, an icon will appear on the side of the screen (see Figure 3a) to show the current status of the carbon budget and carbon emissions in the unit of CO_2eq . As users engage with ChatGPT, EcoChat continuously monitors tokens and estimates corresponding carbon emissions, with real-time updates to emission displays. For more detailed information, users can click the icon to open the popup (Figure 3b). Explanations of ChatGPT inference’s emissions and practical advice on reducing emissions can be found via clicking “Learn More About CO_2eq ”, which will redirect users to a page containing the definition of CO_2eq , how the chat with ChatGPT can produce carbon emissions, and how to reduce this carbon impact (see Figure 5c). Moreover, when users click the “See details” option at the bottom of the popup, they will navigate to another page displaying extended historical usage data in bar chart form with daily and weekly views (see Figure 5a and 5b).

4 CONTRIBUTIONS & FUTURE WORK

While our previous work presented and discussed findings from EcoChat’s in-the-wild user study [36], this paper shifts the focus to the design-level contributions and future research directions that emerged from the design process. According to Görücü et al.’s 2025 review of current AI eco-feedback tools through the lens of sustainable HCI [18], existing systems exhibit several limitations. EcoChat’s design effectively addresses these limitations, contributing a meaningful step forward in the field. Specifically, existing tools notably lack user-centered evaluation, with limited empirical investigation into how users under-

stand, engage with, and respond to the feedback in practice. In contrast, EcoChat was deployed in the wild over four weeks, during which we collected extensive user feedback regarding their understanding of the presented information, how they engaged with the tool, their overall experience and reflections, and the impact on their awareness and behavior [36]. Additionally, Görücü et al. highlight that existing AI eco-feedback tools predominantly promote efficiency-oriented strategies, encouraging users to optimize resource consumption and make existing use more efficient, while rarely supporting sufficiency, helping users determine and stay within an appropriate level of AI use. They also note that these tools remain largely individual-focused: providing limited support for collective perspectives. EcoChat responds meaningfully to both of these limitations with its carbon budget feature and collective information. The carbon budget feature resonates with a sufficiency-oriented design by allowing users to define and monitor their own emissions limit. Our user study found that it encouraged reflection on GenAI usage habits and, for some participants, motivated reductions in GenAI use. Meanwhile, the collective information situates individual usage within a broader social context, and our interview findings suggest that this design helped some participants mitigate feelings of individual insignificance regarding GenAI environmental issues. Participants also spontaneously reframed their own environmental impact as part of a collective effort, such as “ant work” that becomes meaningful when accumulated.

Taken together, these design decisions represent a meaningful step forward in addressing the shortcomings of current AI eco-feedback tools, while also surfacing new challenges that point toward directions for future work. First, despite these efforts, the issue of data materialization raised by Görücü et al. has not been fully resolved. The carbon emission information presented in EcoChat remains somewhat decontextualized, and the resulting metaphorical conversions may not always be meaningfully grounded in users’ everyday experience. This was reflected in our user study, where some participants remained uncertain about what the presented figures meant or how significant they were. This suggests a need for more accessible ways to communicate GenAI’s carbon footprint, along with greater contextualization, for instance, specifying where the underlying computation physically takes place or what energy sources it draws on. Participants’ limited understanding of what the underlying data represented also contributed to difficulties in setting carbon budgets, with several reporting that they were unable to establish targets that felt reasonable and aligned with their goals and usage habits. We suggest that the carbon budget approach could be complemented with social comparison mechanisms to better contextualize emission levels. However, such combinations should be designed with caution, given the potential for boomerang effects [38]. Also, inspired by participants’ responses, personalized approaches offer an alternative avenue for setting individual environmental goals, leveraging users’ historical usage patterns and contextual information to derive more tailored budgets. Such approach could take users’ usage habits, stated goals, and other contextual inputs, and automatically compute a suggested budget on their behalf, rather than requiring users to derive an appropriate target themselves, thus making carbon budgeting more accessible. More importantly, current user studies have yet to establish whether many of these design-level decisions are indeed effective in practice. Future work could draw on user-centred design methodologies, such as co-design workshops, to more directly involve users in shaping and validating these design choices.

5 CONCLUSION

To investigate how to visualize and communicate the environmental impact of GenAI usage to end users in an accessible and interpretable way, we designed EcoChat, a Chrome browser extension that visualizes the carbon emissions of ChatGPT interactions in real time. EcoChat is embedded in users’ real use contexts, provides both numerical and metaphorical representations of emissions, and incorporates a carbon budget feature that allows users to set personal goals and compare them with their actual usage. We describe the design process and rationales of EcoChat, with reflections to derive implications for the design of future similar tools.

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