Empowering Users toward Environmentally Sustainable Digital Practices: From Web-Based to Generative AI Interactions

Mathyas Giudici[1][0000-0002-4935-5131], Monica Vitali[1][0000-0002-5258-1893], and Marco Brambilla[1][0000-0002-8753-2434]

Department of Electronics, Information and Bioengineering, Politecnico di Milano, Milan, Italy
[name].[surname]@polimi.it

Abstract. The environmental impact of digital technologies is becoming an increasingly significant contributor to the global carbon footprint, a trend further amplified by the rapid emergence of generative Artificial Intelligence (AI). Despite this, end users remain largely unaware of the emissions associated with their everyday online interactions. This paper presents an approach that promotes environmentally responsible digital practices by combining real-time monitoring of carbon emissions with interpretation-driven awareness delivery, ultimately empowering users. To operationalize this vision, we implemented Carbon Tracker, a browser extension that estimates the energy consumption and environmental impact of web browsing and interactions with AI-powered chatbots. Building on eco-feedback and sustainable HCI principles, the tool visualises carbon usage and offers analytics to support more informed and responsible digital behaviour. A pilot study with a small group of participants assessed usability and the tool's potential to increase sustainability awareness. Results show good usability, positive user experience, and a significant improvement in users' self-efficacy toward environmentally conscious behaviour. While broader ecological attitudes remained stable, participants reported a strong interest and promoted awareness of AI-related emissions. These findings highlight the potential impact of light, in-context feedback tools for promoting sustainable digital practices and lay the groundwork for future, larger-scale evaluations.

Keywords: Green Information Systems · Web-based Interaction · Generative AI · Sustainable Generative AI · Green-awareness · Web Carbon Emissions.

1 Introduction and Approach

The environmental impact of Information Technology (IT) has been recognised as a relevant issue for several years, accounting for approximately 2–4% of global energy consumption and carbon emissions [24]. The recent surge in generative Artificial Intelligence (GenAI) technologies has disrupted the historical equilibrium between computational demand and energy efficiency, with projections estimating a total impact of 13% by 2030 [25]. Unlike traditional Machine Learning, where the environmental cost is concentrated in training, GenAI inference often represents the dominant source of energy consumption due to the high cost of each interaction and the massive volume of user queries directed to platforms such as Claude, ChatGPT, and Gemini [23]. Estimating the true environmental footprint of these systems remains challenging, largely because of the lack of transparent and standardised reporting. A recent Google report estimated the per-prompt energy cost of a single Gemini text generation to be 0.24 Wh (0.03 gCO2e) [14], yet researchers have highlighted that the sheer volume of daily requests results in a substantial cumulative impact [12].

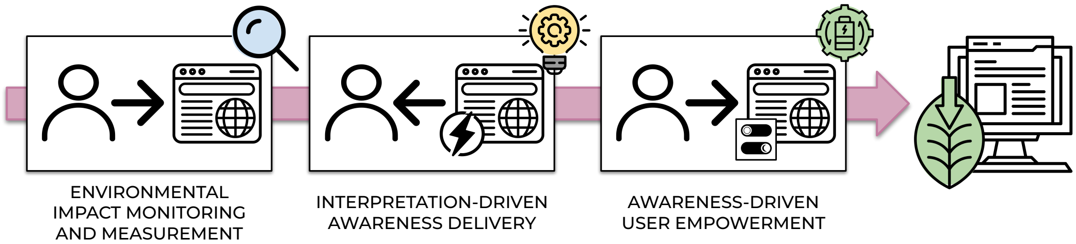

Fig. 1: Approach overview

As users increasingly integrate GenAI chatbots into daily workflows [10], their environmental implications often remain hidden or poorly understood. Prior work has addressed this gap from multiple angles: technical tools such as Carbontracker [4], EcoLogits [28], and LLMCarbon [16] have been proposed to measure AI-related emissions, while Human-Computer Interaction (HCI) research has explored eco-feedback systems [11,2] and persuasive technology [27,18] to promote sustainable digital behaviours. Particularly relevant is GPTFootprint [20], a Chrome extension that visualises ChatGPT's environmental cost in real time; a 7-day study showed increased user awareness, though limited behavioural change, as participants perceived AI utility to outweigh its environmental cost.

This paper advocates for enhancing users' awareness of the environmental footprint of their interactions with web-based technologies, with the ultimate goal of promoting more responsible and sustainable digital behaviours. To articulate this vision, we introduce a methodology consisting of three connected elements that structure a Green Web awareness journey [6,9] (Figure 1): (i) *environmental impact monitoring and measuring*, concerned with the identification and computation of meaningful metrics capturing the environmental cost of users' web interactions; (ii) *interpretation-driven awareness delivery*, translating raw numerical indicators into accessible, relatable, and cognitively meaningful forms through real-world equivalents; and (iii) *awareness-driven user empowerment*, enabling users to take informed actions to directly reduce their environmental impact, such as moderating usage patterns or adjusting service quality. Together, these elements aim to establish a virtuous cycle reducing the environmental impact of web technologies both directly, by lowering per-user energy consumption through behavioural change, and indirectly, by encouraging service providers to adopt more energy-efficient solutions in response to a more sustainability-conscious user base.

To implement this methodology, we developed a browser extension designed to estimate and communicate the carbon footprint of: (i) traditional web browsing, and (ii) AI-driven conversations with ChatGPT, as these activities are widely familiar to non-expert users. We then conducted a pilot study (N=10) to assess the tool's effectiveness and user experience. The main contributions are: (i) a methodology to foster awareness of the environmental impact of web interactions; (ii) an intuitive tool for tracking online activities and estimating associated emissions; and (iii) a preliminary user study evaluating usability, user experience, and potential to raise awareness about digital sustainability.

The remainder of this paper is structured as follows. Section 2 details the developed tool. Section 3 describes the study design, Section 4 reports the results, Section 5 discusses the outcomes, and Section 6 concludes the paper.

2 A browser extension for Web Environmental Awareness

In this section, we describe the implementation of a tool designed to increase users' awareness of the environmental impact of digital practices through real-time monitoring of the carbon footprint of users' interactions. Based on the inputs from the literature and the approach described in Section **??** and other tools[1] available on Chrome Extensions Store, we propose *Carbon Tracker*. The tool is implemented as a browser extension, making it easy to install and use. It allows users to monitor both their web activity and interactions with ChatGPT, offering real-time feedback on the associated environmental impact. The overarching aim of the Carbon Tracker is to raise awareness by visualising energy use and emissions, and to provide meaningful analytics that can help users adopt more sustainable digital habits depending on the specific context of use. Figure 2 offers a snapshot of the plugin interface; in the supplementary material, a table is reported to visually show the difference of Carbon Tracker compared to other existing web extensions.

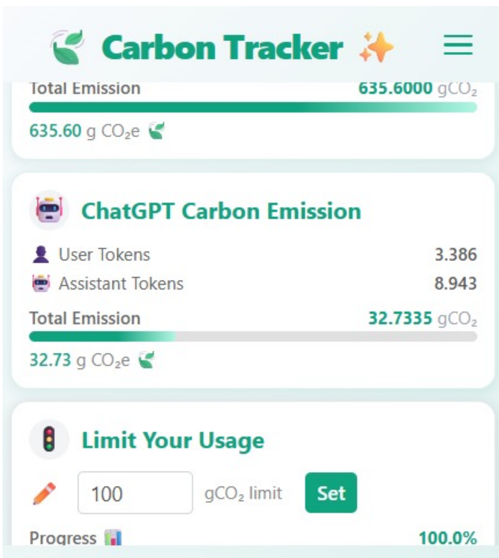

Fig. 2: Snapshot of Carbon Tracker.

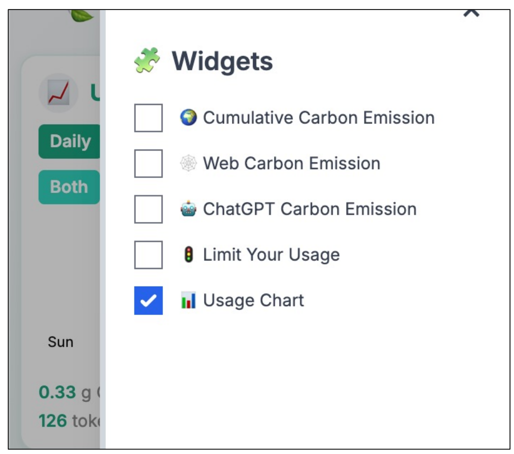

Fig. 3: Carbon Tracker menu to select the different widgets in the Chrome Extension.

2.1 User Interface

The User Interface was designed to provide a clear and high-level overview of both ChatGPT and web-related activity; Carbon Tracker is composed of two core components, namely Extension and Floating Window.

[1] Specifically, *ChatGPT Carbon Tracker* (available on Chrome Web Store) and *Carbon-Calculator* (available at: Chrome Web Store).

Extension. It consists of a Chrome Extension that, once clicked, opens a pop-up where different widgets can be added/removed based on personal or experimental preference (the widgets in the Extension menu as shown in Figure 3). The widgets are:

- *Web Carbon Emissions* gives a view of the total carbon emissions produced by visiting pages on the browser.
- *ChatGPT Carbon Emissions* gives a view on the total carbon emissions produced by ChatGPT. It is based on the total number of tokens (i.e., input and output) and calculates the amount of energy consumed (details of the estimation in Section 2.2).
- *Cumulative Carbon Emissions* provides information on the total carbon emission by summing the *Web Carbon Emissions* and *ChatGPT Carbon Emissions*.
- *Limit Your Usage* enables the user to set a limit target of gCO_2 and shows a progress bar to track the progress.
- *Usage Analytics* offers a bar chart representation delineating the gCO_2 emissions (see Figure 4). Users have the option to visualise Web Carbon Emission, ChatGPT Carbon Emissions, or the cumulative emissions. Additionally, data can be aggregated and presented on a daily, weekly, or monthly basis.

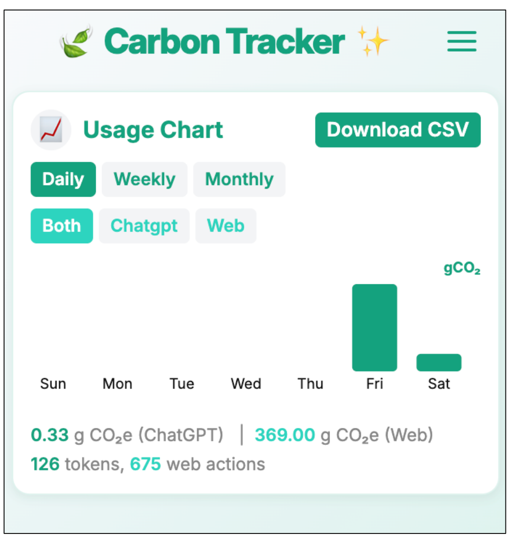

Fig. 4: Usage Analytics widget of Carbon Tracker.

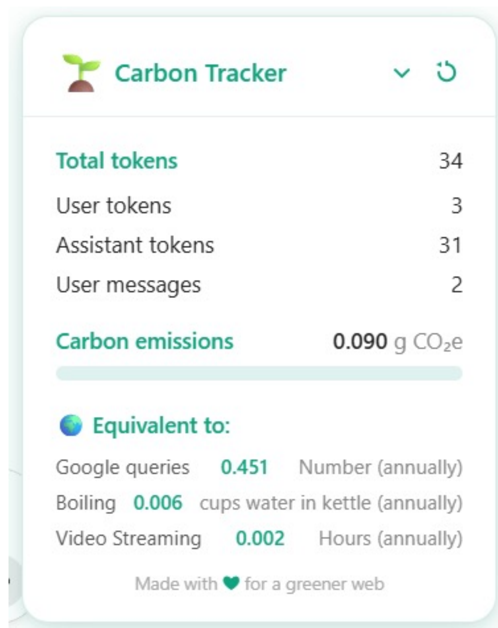

Fig. 5: Floating Window for ChatGPT page provided by Carbon Tracker.

Floating Window. It is a small pop-up (see Figure 5) that appears at the bottom of the ChatGPT interface, showing the analytics of usage of that particular conversation. It also shows the number of input and output tokens and the equivalence of current usage to other daily life tasks (e.g., boiling water in a kettle, watching video streaming).

2.2 Estimations and Implementation

For calculating the web carbon emissions, we used average data available and publicly disclosed. Specifically 0.6 gCO_2 per web-page visited (based on WebSiteCarbon[2]) and additional 0.2 gCO_2 to be put for web-search (based on Google Search[3]). Regarding ChatGPT carbon emission, the extension calculates the number of input and output tokens. The number of tokens is then taken into consideration to calculate the power usage. This differs from model to model, as every model has different active parameters. Then this power usage is multiplied by carbon intensity to get the total carbon emissions. In our specific setting, we used:$EnergyUsage(Wh) = TotalTokens * WattToken$ and $CarbonEmission(gCO_2) = EnergyUsage * CarbonIntensity$ where $WattToken$=0.0045, considering ChatGPT3.5-turbo (data available at the time of the study), while 0.59 as $CarbonIntensity$ factor for the Europe region.

The extension was developed using React with TypeScript for both the pop-up and the floating window. Integration with Chrome APIs enables core functionality through local storage for data persistence and tabs/web interaction. The user interface styling combines Tailwind CSS with custom styles to create an accessible and visually cohesive experience. To support scientific reproducibility and transparency, the complete source code and a direct link to the extension are publicly available[4].

3 Empirical Evaluation

To gain initial insights into the effectiveness and perceived experience of Carbon Tracker, we conducted a pilot experimental study involving 10 participants. Even if the study was conducted in an experimental setup, we asked participants to perform experimental tasks closely aligned with their real-life duties. The study aimed to investigate the following research questions:

RQ1 What is the *effectiveness* of Carbon Tracker in creating sustainability awareness through web-based pages and AI tools?

RQ2 What is the *user experience and usability* of Carbon Tracker in creating sustainability awareness through web-based pages and AI tools?

3.1 Research Variables

The study involved the collection of both quantitative and qualitative data through questionnaires filled out by participants involved in the study. Participants responded to quantitative questions by giving a score on a 7-point Likert scale. A Likert scale is a standard questionnaire format where respondents indicate their level of agreement with statements. For example, a score of 1 might mean ‘Strongly Disagree’ while 7 means ‘Strongly Agree’. This allows us to quantify subjective opinions and experiences.

From an *environmental sustainability* point of view, in order to investigate our first research question (RQ1), we used standardized and validated psychometric instruments (or their adapted versions) commonly adopted in scientific literature on environmental psychology. Such instruments guarantee robustness in terms of reliability and validity of the result, reducing measurement bias

[2] www.websitecarbon.com
[3] sustainability.google
[4] Available at GitHub: `https://github.com/Shubham1632/CarbonTracker` and Chrome Web Store: `https://chromewebstore.google.com/detail/carbon-tracker/pnppibgcmfncfhjfjdkmibdmdhaadahc`

and allowing comparison with previous work. In particular, we measured: **Self-efficacy (SE)** [17] (α=.649) assesses participants' confidence and capacity to adopt sustainable behaviours, as well as whether they felt empowered or capable of making ecologically responsible decisions. **Action Effectiveness (AE)** [17] (α=.860) evaluate participants' assessments of the effectiveness of their own efforts in contributing to overall environmental sustainability. textbfNew Ecological Paradigm (NEP) [3] (α=.666) evaluates participants' agreement with eco-friendly values and their view of the relationship between humanity and nature.

To gather insights on the *User eXperience (UX) and Usability* perceived by participants while using the system and answer RQ2, we took the following metrics from the literature: **User Experience Questionnaire (UEQ)** [26] (α=.746) has been utilised to gather feedback regarding the User Experience (UX) of an interactive digital tool. Among the two versions proposed by [26]. **System Usability Scale (SUS)** [7,5] (α=.869) was used to get participants' perceptions of the system usability.

In addition, more qualitative questions (e.g., previous competencies in AI) and open-ended opinions were gathered. The full script of the questionnaire is provided in the supplementary material.

3.2 Participants

The study involved 10 subjects (6 females and 4 males) with a median age of 48.5 years (range 35-60, M=46.900, SD=7.430). All participants signed a consent form explaining the procedures, objectives, and data treatment; they were all recruited voluntarily and without receiving any financial compensation. The University Ethical Committee approved our research. Participants were recruited during a "Staff Training Week", a university-related training week for both academic and technical administrative staff and involving different European public institutions.

3.3 Procedure

The procedure of the empirical study is divided into different steps. First of all, we collected demographic information from participants, especially their age and gender, and provided each participant with a pseudonymous ID to protect their anonymity. This ID was then utilised consistently throughout the trial to map each participant's replies in both the pre- and post-evaluation periods. For the pre-evaluation, we sent all participants a questionnaire to be completed at least 5 days before the testing. During the pre-evaluation, participants were asked about questions to assess their prior experience with Artificial Intelligence and to answer questions on *environmental sustainability* previously described in Section 3.1. Conducting a pre-evaluation is essential to establish an unbiased baseline for each participant, enabling the assessment of the pre-existing differences in knowledge, attitudes, and perceptions. Such a baseline enables isolating the effects of the intervention more accurately and strengthens the validity of the findings. The experiential part of the study was divided into three main stages and took place in a room at our university. First, participants were asked to perform two tasks (writing a newsletter to announce an event and summarising a presentation). They were then introduced to Carbon Tracker, and asked to complete two more tasks with the tool installed on their browser. The two tasks were: replying to an email (written in a language different from their native language) and writing a document aiming to promote a staff week within their organisation. All documents related to the tasks are available in the supplementary materials. It is worth noting that the tasks were deliberately framed around participants' working contexts (e.g., replying to an email or drafting a summary) to foster ecological validity and minimise the

Hawthorne effect, reducing the risk that participants would alter their behaviour simply as a result of being observed [22]. While the specific instantiation of each task was tailored to resemble familiar professional scenarios, the underlying capabilities under evaluation (e.g., cross-lingual communication, text editing, and summarisation) reflect generic LLM functionalities that are not inherently tied to any particular domain. Consequently, the specific task prompts could be readily adapted to suit alternative professional or educational contexts without affecting the validity of the constructs being measured. After the evaluation, each participant completed the assessments of UX experience and environmental attitudes, answering all the research variables, metrics, and more open-ended questions for general feedback on their experience.

3.4 Methodology and Data Analysis

We employed JAMOVI software to calculate scores and conduct two statistical analyses. First, we calculated descriptive statistics: basic summaries like average scores and variance in participants' responses. This gives us an overall picture of participants' experiences and attitudes. Second, we performed a paired samples t-test to determine whether the changes between pre- and post-evaluation were statistically significant. This statistical test is specifically designed for situations where the same people are measured twice (before and after an intervention). It helps us determine whether any observed changes are likely to be real effects of using the tool, rather than random variation or chance. In more practical terms, if the test shows a 'significant' result, we can be reasonably confident that the tool actually changed participants' attitudes or confidence levels regarding sustainability.

4 Results

This section presents a summary of the findings from the analysis of questionnaire responses submitted by users. Section 4.1 details the participants' backgrounds. Section 4.2 explores the metrics concerning environmental sustainability, while Section 4.3 investigates the variables related to system usability and the participants' comments.

4.1 Participants Background

As outlined in Section 3.3, participants were asked to provide information about their background, focusing on their perception of technology, understanding, and usage of Artificial Intelligence (AI).

Participants reported that technology had an overall impact on society (M=4.500, SD=1.269), and all of them reported having heard the term Artificial Intelligence or AI. In addition, eight of the participants stated that they were able to explain the term, while the remaining ones declared that they 'roughly' knew what the term means, but it's difficult to explain.

Almost all the participants (9 out of 10) declared that their institution uses AI, while only one reported that they do not know if the institution is implementing the usage of AI. In addition, within our poll of participants, 6 of them declared to work with AI, while the other reported only interacting with AI. Looking to the future, participants reported that it is very likely within the next 10 years that their work will require direct interaction with or at least involve AI (80% very likely, 10% somewhat likely, and 10% neither likely nor unlikely).

Looking at the qualitative data about the way participants declare to interact with AI, we observed several trends, particularly involving OpenAI GPT models (i.e., ChatGPT or Microsoft

Copilot). The majority of participants use ChatGPT multiple times daily, primarily for tasks like writing emails, project applications/reports/descriptions drafting or editing, as well as summarisation of slides or reports. One participant reported employing ChatGPT for specific coding tasks, in particular for drafting SQL and DAX snippets. Some individuals also reported using other AI providers, such as Le Chat (a.k.a. Mistral) and Perplexity.

Interestingly, a few participants reported "[to use Copilot for] finding and compiling information on a specific topic", noting how AI has become available in various web tools (e.g., search tools, Microsoft Office and Google suites, etc.). One participant, for example, commented how "[ChatGPT] It's more sharp than Google or Safari to find answers, but it's not often", while another one directly referred to Google AI Overviews by saying "whenever I google something on my laptop or search something on my phone, the first results I get are offered by AI automatically".

4.2 Environmental Sustainability

In our initial examination of the questionnaire data, we computed the mean values for SE, AE, and NEP for both pre-evaluation and post-evaluation conditions. To evaluate the normality of these distributions, we utilised the Shapiro-Wilk test, finding no deviation from normality for all the metrics. For the sake of completeness – given the small sample size (N=10) – we nevertheless report the results of both parametric and non-parametric tests.

Table 1 presents the descriptive statistics for environmental sustainability metrics. In the *pre-evaluation*, subjects declared an average *self-efficacy* in green domestic behaviours of 4.233 (SD=0.738), while their *action effectiveness* was attested to 5.800 (SD=0.958). The *NEP* test presented an average value of 5.507 and a standard deviation of 0.430. In the *post-evaluation*, we observed the *SE* with an average of 4.767 (SD=0.704). *AE* presents a mean value of 5.300 (SD=1.674), while *NEP* shows an average value of 5.580 (SD=0.622).

Table 1: Descriptive results of the pre- and post-evaluation of environmental sustainability metrics.

Metric	***SE***	***AE***	***NEP***
Pre AVG	4.233	5.800	5.507
Pre SD	0.738	0.958	0.430
Post AVG	4.767	5.300	5.580
Post SD	0.704	1.674	0.622
Shapiro-Wilk W	0.919	0.902	0.883
Shapiro-Wilk p	0.350	0.229	0.143

Table 2: Paired Samples t-Test

			Statistic	**df**	**p**
pre-SE	post-SE	Student's t	-2.331	9.000	0.045
		Wilcoxon W	8.000		0.052
PRE-AE	POST-AE	Student's t	1.449	9.000	0.181
		Wilcoxon W	27.500		0.207
PRE-NEP	POST-NEP	Student's t	-0.729	9.000	0.485
		Wilcoxon W	20.000		0.492

Note. H_a $\mu_{Measure1-Measure2} \neq 0$

To determine if the observer measures for environmental sustainability were statistically significant, we used the Paired Samples t-Test. The study found a significant main effect for *self-efficacy*, t(9)=-2.331, p=0.045, showing a statistically significant improvement [5] in SE values (see Figure 6). There was no significant difference between pre- and post- results of *AE* and *NEP*. Table 2 reports the complete results of the statistical test run.

[5] tending to significance for Wilcoxon's non-parametric test with W=8, p=0.052.

Table 3: Descriptive results on user experience and usability

	Variable	AVG	SD
UEQ	obstructive | supportive	6.100	0.994
	complicated | easy	6.200	1.317
	inefficient | efficient	6.300	0.949
	confusing | clear	5.600	1.430
	boring | exciting	5.800	1.398
	not interesting | interesting	6.200	1.135
	conventional | inventive	5.600	1.776
	usual | leading edge	5.100	1.663
SUS	SUS	75.571	12.444

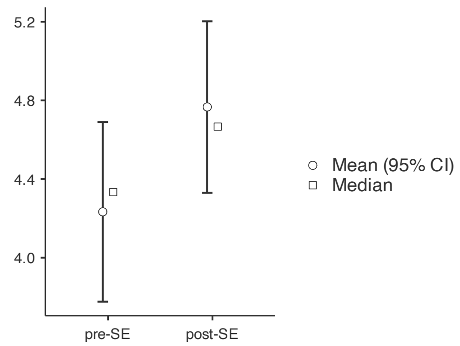

Fig. 6: Self-efficacy (SE) pre- and post-evaluation Plot.

4.3 User eXperience

Descriptive variables regarding the interaction with the system, subjects were generally satisfied with the user experience with a *SUS* score of 75.571/100 (SD=12.444). The average mean value for the *UEQ* scale is 5.862 with a standard deviation of 1.020. Given such a score, this result suggests that participants had a positive perception and user experience of the tool. Table 3 provides a detailed view of the results on the different items of the UEQ questionnaire.

5 Discussion

The first implication that can be highlighted from this study is that Carbon Tracker or browser extensions/pop-ups are promising tools to help users to be more ecologically conscious. Such implication is provided by the rise of the *Self-efficacy*, which is directly related to users' perceptions of their own ability to reduce their energy use. Thus, the outcome suggests how carbon emission-related extensions may assist users in monitoring their regular web activity – especially such activities that involve the usage of an LLM – and raise their level of environmental consciousness. This particular effect on self-efficacy aligns with previous work in the literature on other eco-feedback applications [17,19,8,1] but extending such past work with a novelty factor, as it is delivered by a tool that does not represent a new interaction interface (e.g., VR/AR, chatbot, etc.) but by a simple interaction in the same browser with little impact on the overall experience of the internet navigation (cf. [30,20]).

In addition, it is essential to consider that participants reported high levels of environmental consciousness, which helps explain why other environmental sustainability criteria – not focused on direct action – did not increase. Specifically, the *NEP* test, which evaluates deeply held personal beliefs about sustainability and climate change, may be less sensitive to change after a single interaction with Carbon Tracker. Such opinions on sustainability are typically stable and difficult to influence by short interventions [29]. Similarly, there were no appreciable differences in the measure of *Action Effectiveness*. Since the nature of the questions, which covered more general daily activities rather than referring to the web interaction or the experimental setup, may be the cause of the lack of noticeable difference, as well as the short intervention nature of the study (cf. [29,17,19]).

The average SUS score for usability was 75.571. Thus, according to [5], the usability of our system is acceptable, with a grade of C and an adjective rating between 'good' and 'excellent'. In addition, looking at the user experience, the UEQ confirmed a good rate on the way participants perceived the experience with the tool, allowing us to articulate that Carbon Tracker was found 'supportive', 'easy', 'efficient', and 'interesting'.

The adjective 'interesting' also emerged from the qualitative responses of participants. In particular, one of them stated: "I found it interesting, and [it] helps to raise awareness of the impact of AI usage" showing how carbon footprint data and their visualisations can effectively engage users and promote environmental consciousness regarding their AI interactions. Another participant said: "It was fascinating and scary to see how much CO2 was emitted", highlighting how the interest in carbon emissions was coupled with concerns, as the user confronted the tangible environmental costs of their AI usage. Similarly, a participant reported: "I found it interesting, and [it] helps to raise awareness of the impact of AI usage", while another one highlighted how she/he was "able to count and be aware of the cost of energy that implies generative AI". It appears that all extant results are proportional to the novelty and interest effect also reported in the works of [15,30,21], which investigate the effect of feedback on carbon emission related to web navigation. However, compared to [20], there is a difference in the emotional reactions; GPTFootprint elicited strong negative emotional responses such as guilt and shock, while in our case (i.e., Carbon Tracker), even participants expressed some concerns about the AI emission, but they reported them in a more neutral or overall positive reaction.

In general, some participants also appreciated the possibility of having "an overview of [my] carbon footprint on web search and ChatGPT". Thus, Carbon Tracker design was valued as it provided separate visibility into two distinct aspects of digital consumption: the environmental impact of regular web browsing activities and that associated with AI-powered tools. By distinguishing between these two sources, participants could better understand how different online behaviours contribute to their overall carbon footprint, echoing previous work highlighting the trade-off between performing a certain activity and the carbon emission related [15,13]. In addition, one participant specifically highlighted how striking it was to observe how quickly AI usage caused CO2 emissions to rise, noting the particularly significant environmental cost associated with AI-powered interactions compared to traditional web activities. This last comment from the participant also reveals how Carbon Tracker could be a valid solution for quantifying the environmental cost of GenAI models, which are increasingly widespread and partially substituting/integrating in search engines (as also noted by a participant in the previously cited comment "whenever I google something on my laptop or search something on my phone, the first results I get are offered by AI automatically").

Overall, it should be noted that the encouraging results obtained are likely facilitated by Carbon Tracker's design as a browser extension, which embeds carbon footprint monitoring directly within users' natural web browsing experience. Thus, such findings suggest that future work should further explore the effectiveness of such seamlessly integrated tools in promoting sustained environmental awareness (cf. [30]).

6 Conclusion

This paper introduced Carbon Tracker, a browser extension designed to raise awareness of the environmental impact of both web browsing and generative AI usage. Our pilot study showed that the tool is usable, positively perceived, and capable of increasing users' self-efficacy regarding sustainable behaviours. The study's limitations include the fact that it was run on a small, homogeneous sample of users. However, it is worth reporting that it is a novel sample of users in terms of age and background compared to previous work in the field (cf. [20]). Other limitations are on the short-term evaluation and the evaluation of only ChatGPT among the Generative AI tools. In terms of user impact, deeper ecological beliefs and perceived action effectiveness did not change significantly, likely due to the short-term intervention and high baseline attitudes. Future work should involve broader and longer-term studies, extending the tool to additional AI platforms, and exploring whether such feedback can lead to sustained behavioural change. Despite the study limitations, the results suggest that real-time eco-feedback delivered by a web extension can meaningfully support users in becoming more conscious of their digital carbon footprint, in contrast to previous work (cf. [30]). Participants highlighted how seeing the contrast between ChatGPT emissions and regular browsing clarified the specific burden of GenAI. Thus, Carbon Tracker highlights the potential of integrating environmental feedback via browser extension directly into everyday working digital interactions (with browsers) to promote more sustainable online practices.

Acknowledgments. The authors would like to thank all the participants involved in the study and the members of the Staff Exchange Office of the Politecnico di Milano. They also extend their gratitude to Juan Camuyrano, Natalia Dolkowskais, Shubham Gangurde, and Ilaria Struppa for their valuable work in the development of Carbon Tracker.

Supplementary Material The supplementary material is available at: `https://doi.org/10.5281/zenodo.19892003`.

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