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RESEARCH ARTICLE

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Client-side energy and GHGs assessment of advertising and tracking in the news websites

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Abstract

Electronic devices consume energy both in the production and the use phase. Furthermore, the "hidden" impacts linked to their use are not frequently assessed and they depend on the behavior of the users, besides the servers and complex web networks. It must be underlined that many websites employ ads and trackers as part of their monetization strategy and, in order for online ads and trackers to work, they add an additional code to be executed on the users' machines, which in turn requires more processing power. Considering that the Internet had an estimated 4.9 billion users in 2021, the global energy and carbon impacts of online ads and trackers might be significant. To investigate this phenomenon, we designed a novel automated framework for bottom-up estimation of greenhouse gas (GHG) emissions attributable to software using exclusively free and open source software. Our process involved the building of a random sample of global news websites which we visited with and without an ad-blocker, each time collecting power usage in identical conditions. The gathered data were put into an ordinary least squares (OLS)-based linear regression model, which showed that ads and trackers on news websites require on average an additional 6.13 W of power on personal computers. This result was then tuned to global environmental and technological parameters to estimate that in 2019, on the client side, ads and trackers on the news websites consumed 0.61 TWh of electrical energy, emitted 0.29 $MtCO_2eq$ of GHG, and cost all Internet users approximately 140 million USD (purchasing power parity) of electrical energy. This article met the requirements for a gold-gold JIE data openness badge described at http://jie.click/badges.

KEYWORDS
bottom-up methodology, energy consumption, GHG emissions, ICT, industrial ecology, online advertising

1 | INTRODUCTION

The environmental impact of the Internet cannot be easily ignored when, according to the United Nations, there were an estimate 4.1 billion Internet users in 2019 (ITU, 2022), the majority (53%) of the 7.7 billion people living on Earth at that time (UN DESA, 2019).

Energy-related greenhouse gas (GHG) emissions are one of the drivers of climate change. The information and communication technology (ICT) sector has high impacts due to electricity consumption equivalent to 3.6% of the global electricity consumption and GHG emissions equivalent to 1.4% of the global carbon footprint (Malmodin & Lundén, 2018; Obringer et al., 2021).

Measurement of GHG emissions is an important topic in industrial ecology and a fundamental step in life-cycle impact assessment. Due to the complexities of networks and the decentralized nature of the Internet, it is hard to assess its overall environmental impact. For this reason, many studies circumscribed their scope to specific countries (Baliga et al., 2009), whereas others have focused on specific aspects of the Internet, such as video streaming (Shehabi et al., 2014) and telecommuting (Hook et al., 2020). This study too focuses on the environmental impacts of a specific application of the Internet: ads and trackers on the World Wide Web.

The web is made up of servers, which store and deliver content, and clients, which display content to the end users (Open University, 2020). For our study, based on a bottom-up approach, we decided to focus on the client side. With the growth in complexity of the HTML standard and web browsers, clients moved from static text and images to audio and video (University of Washington, 2011). Thanks to the evolution of JavaScript, the programming language in which client-side scripts executed by web browsers are written, and Cascading Style Sheets (CSS), the domain-specific language used to format webpages, websites became more and more interactive and started resembling standalone applications.

Ads greatly benefited from the Internet's multimediality and interactivity. Additionally, unlike traditional advertising, web ads can execute code on the user's browser (Sood & Enbody, 2011). This allows advertisers to collect information to target specific users, a practice called online behavioral advertising (Boerman et al., 2017). This kind of tracking can be very accurate thanks to fingerprinting techniques, which can be used to identify a specific user out of many (Englehardt & Narayanan, 2016; Vastel et al., 2018).

Despite the claims that online behavioral advertising and tracking help deliver ads which the users might find more relevant (Google, 2021), some users find ads irritating and/or detrimental to their privacy (Moore et al., 2015). To address concerns related to advertising and web monitoring, two major innovations, one legal and the other technological, have been launched.

From the legal perspective, the EU has adopted the General Data Protection Regulation (GDPR), a law which allows users to deny permission to some kinds of tracking (European Parliament, 2016) via "consent popups."

On the technological side of things, ad-blockers have been built. Ad-blockers are programs (usually browser add-ons) which prevent ads (and often trackers too) from running on browsers (Söllner & Dost, 2019). Ad-blockers have been adopted by nearly one fifth of web users (Malloy et al., 2016) and some browsers (like Brave) have started including them by default.

The popularity of ads and the effectiveness of modern ad-blockers were the key for this study, in which the energy, GHG emission and cost differentials of browsing websites with and without an ad-blocker are assessed from a bottom-up perspective.

Such an assessment is not straightforward, as servers communicate not only with clients but also with other servers (Pujol et al., 2014).

For this reason, we set some boundaries to our study. Since we decided to follow a bottom-up approach based on primary data, we chose to circumscribe our study to the end-user's device, which we could fully operate ourselves. We also focused exclusively on a niche of websites belonging to the news category, which often feature ads (Budak et al., 2016) and trackers (SolarWinds, 2018).

In comparison with previous studies which tried to estimate the environmental impacts of online ads, our study brings the novelty of implementing a client-side, time-allocating (unlike Pärssinen et al., 2018), entirely software-based (and not equation-based like Pearce, 2020) bottom-up methodology for appraising energy usage by computer programs. Particularly, our contribution is threefold: (i) to establish an entirely software-based reproducible methodology for assessing energy use by computer programs using exclusively free/libre and open source software (FLOSS); (ii) to identify the client-side environmental impacts (and their economic effects) for the popular news category of websites; (iii) to provide further empirical evidence that consumer choices can affect positively the environment.

2 | MATERIALS, DATA, AND METHODOLOGY

This study follows a three-step methodology (Figure 1):

1. Data collection: a random sample of news websites was built. Data about the power differential between browsing the sampled websites with and without ads and trackers was collected;
2. Econometric analysis: an OLS-based linear regression model was used to estimate the impact of ads and trackers on jointly central processing unit (CPU) and graphical processing unit (GPU) power usage;
3. Scenario analysis: power usage was converted to energy consumption according to average Internet browsing times. Average global coefficients were applied to energy estimates to assess the amounts of electrical energy consumed, their cost and the amount of CO_2-equivalent emissions attributable to ads and trackers on the client side. Global projections were used to hypothesize three scenarios (as in Erdmann, 2010) estimating global energy consumption and CO_2-equivalent emissions attributable to ads and trackers on the client side. The *baseline scenario* hypothesizes a browsing time of 10 min on a mix of devices, mobile (59%), and desktop computers (41%); the *mixed-device scenario* keeps the mix of used

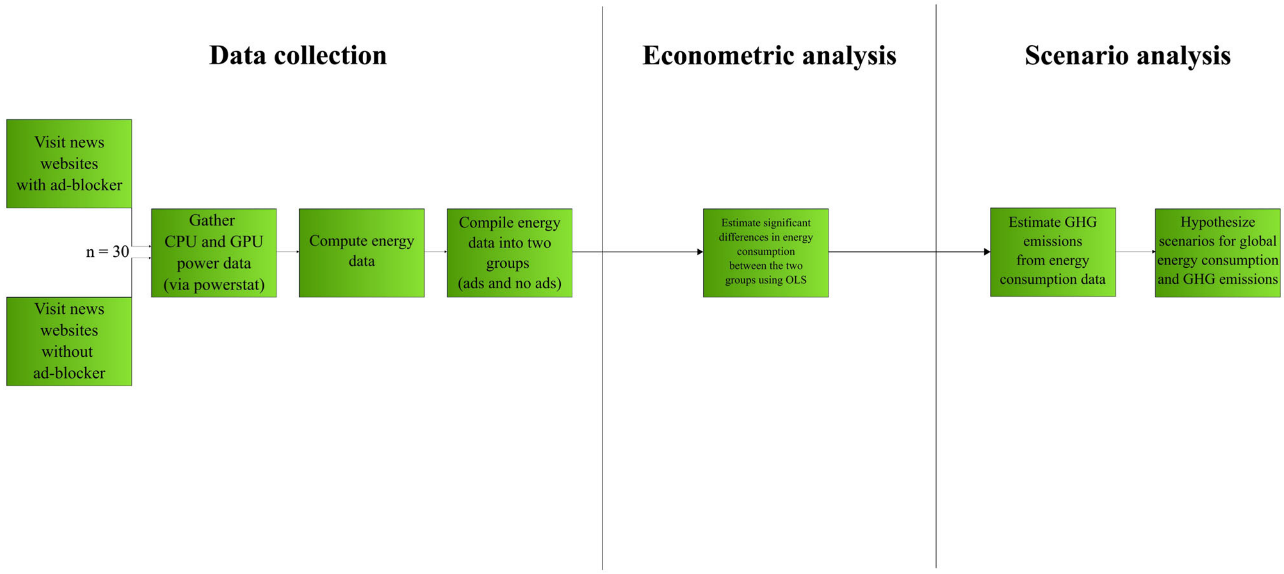

FIGURE 1 Three-step methodology to measure GHG emissions of online ads and trackers (original work)

devices of the baseline scenario while increasing the web browsing time to 3.3 h; the *computer-only scenario* keeps the web browsing time of the *mixed-device scenario* but hypothesizes that personal computers are the only used devices.

This methodology provides a generalized framework for conducting bottom-up assessments of software-generated energy consumption.

2.1 | Data collection

In this phase, primary data regarding CPU and GPU power usage was collected by visiting websites in our sample with and without an ad-blocker.

2.2 | Hardware and software setup

Thanks to the advancements in computer technology, it is possible to measure CPU and GPU power usage without using external hardware meters. This, however, is only achievable by using a processor which includes a power-metering interface. One such interface used in this study is RAPL by Intel (Czarnul et al., 2019; Intel, 2014), which makes estimates that have been shown to closely match actual power usage by its maker (Rotem et al., 2012).

The computer used in our experiment was bought in 2014 (specs in the Supporting Information).

For increased reproducibility (Ince et al., 2012), only FLOSS is used (listed in the Supporting Information).

Powerstat (King & Geerinckx-Rice, 2021) is a program that queries RAPL to generate a human-readable report containing power usage statistics.

The web browser we used to conduct our experiment, Chromium, is the FLOSS version of Google Chrome, which is used by the estimated majority (65.96% as of January 2021) of desktop users (StatsCounter, 2021). Other web browsers such as Microsoft Edge (Microsoft, 2020) and Brave (Brave, 2018) are based on Chromium, so the percentage of users of Chromium-based browsers is even higher.

uBlock Origin (uBO) is a popular ad-blocker for Google Chrome (Chrome Web Store, 2021) and Mozilla Firefox (Mozilla Firefox Addons, 2021). uBO was chosen for this experiment because it claims to focus on CPU and memory efficiency (Chrome Web Store, 2021). In addition, uBO is frequently updated (Github, 2021) and thus can be expected to keep up with the changes in ad and tracking technology.

Before conducting any further experiments, a benchmark was needed to correctly understand the results. For this purpose, the power usage of Chromium with and without uBO was tested on the about:blank empty page. The difference, as shown in the Supporting Information, was not deemed significant.

Finally, since trackers can collect information about user interest by following the mouse cursor (Huang et al., 2011), a Rust program called *move_mouse* (in the Supporting Information) was written to automate mouse movement so that it always repeats the same pattern.

TABLE 1 Random sample of global news websites, sourced from 4imn.com (2019a)

Website	Rank	Country
Kompas	5	Indonesia
Liberty Times	6	Taiwan
El País	12	Spain
Malayala Manorama	16	India
The Sydney Morning Herald	43	Australia
The Indian Express	45	India
The Times	52	UK
Chosun Ilbo	53	S. Korea
Las Últimas Notícias	58	Chile
Rossiyskaya Gazeta	71	Russia
Evening Standard	72	UK
Arizona Republic	100	USA
Sabah	103	Turkey
Detroit Free Press	115	USA
Daily Star	133	UK
Der Tagesspiegel	140	Germany
The Philadelphia Inquirer	141	USA
The Star Online	142	Malaysia
Il Sole 24 Ore	148	Italy
Handelsblatt	154	Germany
San Francisco Chronicle	162	USA
Herald Sun	168	Australia
The Detroit News	171	USA
Investor's Business Daily	173	USA
Dnevni avaz	175	Bulgaria
The Jakarta Post	180	Indonesia
Diário Libre	184	Dom. Rep.
Expansión	188	Spain
The New York Observer	195	USA
Korea Economic Daily	200	S. Korea

2.3 | Data sample

Once the hardware and software setup was established, we needed some websites for our sample. News websites often show ads (Budak et al., 2016), and an informal study estimated an average of 41 trackers per news website (SolarWindows, 2018). For this reason, these websites were deemed appropriate for our study. Global news websites were sourced from 4imn, a directory for top news websites, which in turn sources popular analytics services such as Google Page Rank and Alexa (4imn.com, 2019a), which have been used in the past literature.

We ran some JavaScript code based on CSS selectors from the browser console to scrape 4imn's "Top 200 Newspapers in the World" list (4imn.com, 2019b) and 30 out of 200 websites were randomly sampled.

To ensure that all websites could be used for our experiment, we visited them one by one. Websites which blocked visitors from the EU (since this experiment was conducted in Italy) and those which did not load correctly were discarded and replaced with different ones picked randomly with the same method. Our sample is fully listed in Table 1.

Additionally, it was evident that three websites from the sample (azcentral.com, freep.com, and detroitnews.com) were based on the same content management system (CMS) called Presto (Poynter, 2014), so we decided to take note of its presence for our econometric analysis.

TABLE 2 Description of the variables in the regression model

Variable	Description
y	Dependent variable, sum of the CPU and GPU average power
x_1	Dummy variable for ad-blocking (1 = ad-blocking enabled)
x_2	Dummy control variable for Presto CMS (1 = Presto CMS is used)
u	Error term

2.4 | Power data

The power data for each website was collected on December 21, 2020 by following this algorithm:

1. Open a website and wait for it to fully load. Close all popups, including full-screen ads (which hide the page's content) and GDPR consent prompts (which are accepted at the default settings);
2. Start the *move_mouse* and *powerstat* programs for 60 s via Qterminal with the following command:

```
sleep 2; move_mouse & powerstat -g -R -n 1 60 > $WEBSITE.txt
```

Where $WEBSITE.txt is the filename of the report for a specific website.

A 2 s delay was set to make time for switching from the Qterminal to the Chromium window;

3. Clear all private data (Ctrl + Shift + Del) in order to eliminate behavior based on existing cookies and caches, which would add unpredictability.

This process was repeated for all 30 websites, with and without uBO, for a total of 60 times. No other windows except for Qterminal (minimized) and Chromium were opened. The sampling time was set to 1 min because we considered it sufficient to visit a substantial portion of a web page (at the scrolling speed set by our *move_mouse* utility) and attenuate the effect of spikes and drops (outliers) in CPU and GPU usage.

Each report was saved into a separate text file. Those files were parsed by a script (in the Supporting Information) for averages and standard errors, which it compiled into a single comma-separated values cross-sectional data file. Finally, we manually added a dummy variable which controls for the presence of the Presto CMS to obtain our complete dataset.

2.5 | Econometric analysis

The econometric method we have chosen for this study is linear regression via the OLS technique. We defined the set of variables shown in Table 2. We ran the regression in gretl (Gretl, 2021), a FLOSS package from the GNU project for econometric analysis.

$$y_{it} = \beta_0 + \beta_1 x_{1it} + \beta_2 x_{2it} + u_{it}$$

For linear regression to be used, certain assumptions have to be met (Stock & Watson, 2015). Considering that:

- The sample size is $n = 30$, so the sample can be considered big (Stock & Watson, 2015)
- The chosen websites were randomly sampled from a population of 200 global news websites
- The dependent and independent variables have finite kurtoses
- The intercept term is included in the regression model
- White's heteroskedasticity test could not refute the null hypothesis for the absence of heteroskedasticity at any relevant significance level
- Variance inflation factors are at the minimum possible values, showing no multicollinearity.

Despite the fact that the residuals are not normally distributed, we went on with the asymptotic interpretation of our results.

2.6 | Scenario analysis

In the final step, global projections were calculated from the results of our econometric analysis to hypothesize three distinct scenarios. To achieve this, the following hypotheses were adopted for all scenarios (exceptions noted):

TABLE 3 Linear regression for estimating ad marginal power consumption

Name	Coefficient	Std. Error	*t*-ratio	*p*-value
const	35.1498	1.78755	19.66	4.49e-27 (***)
adblock	−6.12767	2.24585	−2.728	0.0084 (***)
Presto	−9.81759	1.43719	−6.831	6.08e-09 (***)

- Global internet users: 4.1 billion people (ITU, 2022).
- Global average time spent on news websites: 0.16 h per day.
- This figure, equivalent to 9 min and 36 s, was calculated as an average of the average visit duration field from SimilarWeb (based on data from December 1, 2020). Considering that a conservative estimate of daily Internet browsing time amounts to around 3.3 h per day (according to ESS, 2018 for Europe, and Ofcom, 2020 for the United Kingdom), we pose that 4.8% of the total time spent on the web is spent on news websites by every user. We adopted the 3.3 h per day hypothesis for both our mixed-device and computer-only scenarios.
- Average carbon intensity of electricity: 475 g CO_2eq/kWh (IEA, 2019).
- Global average residential energy price: 0.226 USD (PPP)/kWh (IEA, 2018). PPP means purchasing power parity, a method used to eliminate differences in price levels between countries (Eurostat, 2018).
- Shares of web users by device: 41% personal computers, 59% mobile devices (StatsCounter, 2021). We adopted this hypothesis for the baseline and mixed-device; for the computer-only scenario, we adopted the hypothesis of all web browsing happening on personal computers.
- Web browser idle power usage: 13.74 W for personal computers, 0.17 W for mobile devices. The personal computers estimate was gathered directly from powerstat, whereas the mobile one from Thiagarajan et al. (2012).

Additionally, a 365-day year was adopted.

3 | RESULTS

The results from our econometric analysis are shown in Table 3.

Our linear regression, which has an R^2 equal to 0.200828, shows that ad-blocking has a negative effect on conjunct CPU and GPU power usage. On average and at a confidence level of 99%, under our assumptions, browsing news websites without ads and trackers requires about 6.13 W less power per user. In other words, online ads and trackers require about 14.85% of the total power required to normally browse news websites.

By applying the coefficients specified in Section 2, we could make some generalized estimates at the aggregate level. The results are shown in Table 4.

4 | DISCUSSION

4.1 | Contextualizing the results

Online ads and trackers appear to negatively impact the environment by increasing the amount of electrical energy needed to visit websites, which in turn increases the amount of global GHG emissions (Moyer & Hughes, 2012).

According to our *baseline scenario*, the global yearly energy consumption of ads and trackers on news websites (0.61 TWh) is superior to the amount of energy consumed in 2019 by Haiti (0.42 TWh) and South Sudan (0.57 TWh) according to IEA. The global yearly GHG emissions attributable to ads and trackers on news websites (0.29 MtCO_2eq) are higher than Lichtenstein (0.2 MtCO_2eq) and roughly 40% of those emitted by Gibraltar (0.72 MtCO_2eq) and Eritrea (0.77 MtCO_2eq) according to IEA. Other country-level comparisons are made in Figure 2.

These figures reflect an estimate which we consider both realistic and conservative. It only refers to news websites.

For purely speculative purposes, we can imagine two alternative scenarios in which our estimated averages for news websites are extended to all websites. Since we have reason to believe that news websites are particularly aggressive in their ad and tracking tactics (SolarWinds, 2018), we will assume both these scenarios to be pessimistic, even though they could contain some truth.

In the *mixed-device scenario*, we make a projection based on our analysis of online news ads and trackers assuming that visitors spend 3.3 h per day on the Internet (rather than the less than 10 min we used for our *baseline scenario*). More specifically, the assumption of the majority (59%) of Internet users browsing from mobile devices and the rest (41%) on desktop is kept. In the *mixed-device scenario*, ads and trackers every year would consume 12.63 TWh of electric energy, cost all users 2.85 billion USD (PPP) and emit 6 MtCO_2eq of GHG. Some country-level comparisons for energy consumption and emission levels are made in Figure 3.

TABLE 4 Global energy, cost, and environmental impact of web advertising and tracking on news websites

Parameter	Value	Unit of measurement
Personal computers ad power consumption	6.13	W
Global internet users	4.10	billion users
Daily time spent on news websites	0.16	h
Personal computers web browser idle power usage	13.74	W
Mobile web browser idle power usage	0.17	W
Share of personal computers web users	41%	web users
Share of mobile web users	59%	Visitors
Mobile ad power consumption	0.08	W
Ad power consumption	2.56	W
Ad daily energy consumption (user)	0.41	Wh
Ad yearly energy consumption (user)	0.15	kWh
Ad yearly energy consumption (global)	0.61	TWh
Global average residential energy price	0.23	USD (PPP)/kWh
Ad yearly energy domestic cost (user)	0.03	USD (PPP)
Ad yearly energy domestic cost (global)	140	million USD (PPP)
Global average carbon intensity of electricity	475	gCO_2eq/kWh
Ad yearly CO_2eq emissions, all	0.29	$MtCO_2eq$

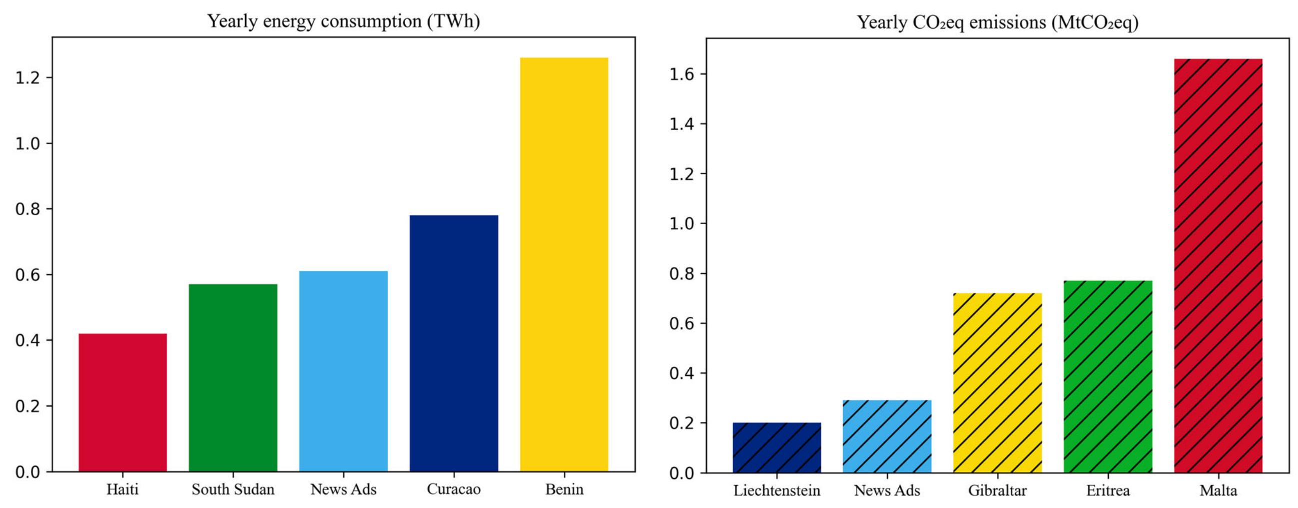

FIGURE 2 Energy consumption (personal elaboration based on IEA data for 2019) and GHG emissions (personal elaboration based on IEA data for 2019 and UNFCCC, 2021) comparison, baseline scenario. The underlying data for this figure can be found in Supporting Information S2.

The next scenario, called *computer-only*, keeps the assumption that visitors spend 3.3 h per day on the Internet and adds the assumption that all (100%) users browse the web on desktop computers. In the *computer-only scenario*, ads and trackers every year would consume 30.26 TWh of electric energy, cost all users 6.84 billion USD (PPP), and emit 14.37 $MtCO_2eq$ of GHG. Some country-level comparisons for energy consumption and emission levels are made in Figure 4.

We also estimated the number of cars which would cause the same amount of CO_2-equivalent emissions in a year during the use phase (while accounting for average European parameters taken from Transport & Environment, 2018):

- Baseline scenario: 160,000 cars
- Mixed-device scenario: 3 million cars
- Computer-only scenario: 8 million cars

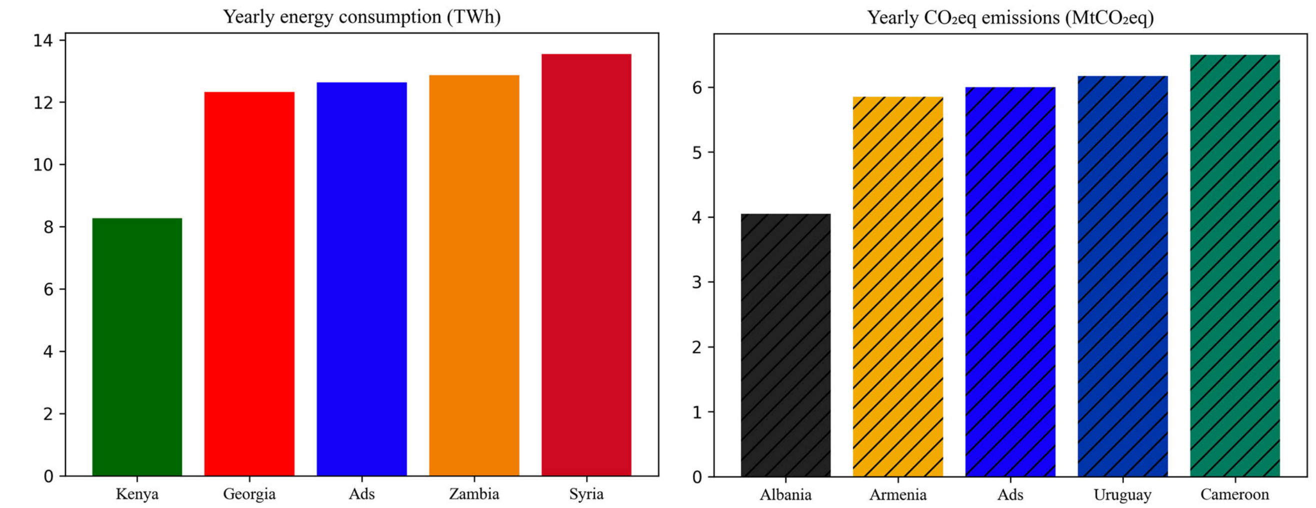

FIGURE 3 Energy consumption (personal elaboration based on IEA data for 2019) and GHG emission (personal elaboration based on IEA data for 2019) comparison, mixed-device scenario. The underlying data for this figure can be found in Supporting Information S2.

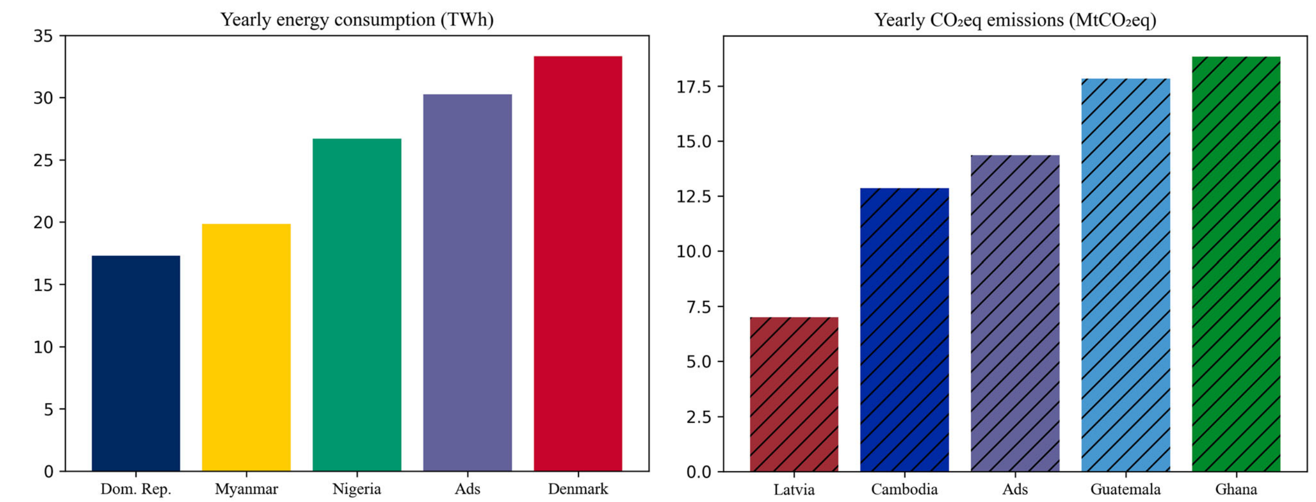

FIGURE 4 Energy consumption (personal elaboration based on IEA data for 2019) and GHG emission (personal elaboration based on IEA data for 2019) comparison, computer-only scenario (personal elaboration based on IEA data for 2019). The underlying data for this figure can be found in Supporting Information S2.

One of our original research goals was to calculate a conservative estimate, so we could mitigate the effects of both uncertainty and choice of equipment.

To achieve this, we chose the lowest possible hypothesis for daily browsing times among reputable sources. When it comes to news websites, we believe our choice to be extremely conservative compared to reality. While it is unrealistic that web users spend all their online time on news websites, the "news" category can be broad enough to include websites tailored to each user's interests (finance, gaming, health, science, sports, etc.). It is also likely that web users visit more than one website fitting the news category. And despite the fact that an informal study has shown that news websites can be particularly aggressive in their ad-showing (SolarWinds, 2018), this does not mean ads and trackers on other kinds of websites necessarily consume less energy.

Our *mixed-device scenario* is most likely an overestimate of the environmental impacts of online ads and trackers due to the ad-intensive nature of news websites. This is only true if "online" is used to refer exclusively to what can be accessed by a web browser. If, however, "online" is used to describe apps which deliver ads from the Internet, including video and audio ads, then our *mixed-device scenario* gains more credibility.

This *computer-only scenario* is unlikely to be realistic. Still, it highlights the difference between personal computer and mobile energy consumption patterns. This could shed some light on what direct environmental impacts could have looked like in the pre-mobile era.

The economic figures we determined only concern direct energy costs for end users. They are, in other words, private costs. Actual costs for society would be much higher, due to the global effects of climate change.

Our results can be compared with the previous literature, even if with some caveats. Previous studies which assessed the environmental impact of online ads did not focus specifically on news websites. For this reason, we cannot compare our more accurate *baseline scenario* results directly with the previous literature. To solve this, we can compare the existing literature to the most conservative among our generalized scenarios, the *mixed-device scenario*.

Our figures are more than twice as big as those by Pärssinen et al. (2018) (in their table 5), which estimates that online advertising, on the client side and without uncertainties, consumes around 5.64 TWh (12.63 TWh in our *mixed-device scenario*) of electrical energy and emits around (adjusted for our lower carbon intensity) 2.68 $MtCO_2eq$ (6 $MtCO_2eq$ in our study) of GHG. Aside from the data gathering method, the biggest difference between the two studies is the allocation method: traffic based for Pärssinen et al. (2018), time based for our study. We believe the differences between those methods to be radical and impossible to reconcile.

Our *mixed-device* figures are certainly more comparable with those of Pearce (2020), another study which uses time-based allocation. Pearce (2020) estimates that using uBO would save 13.5 TWh per year (12.63 TWh in our *mixed-device*) and, when corrected for our higher global average residential electricity price of 0.226 USD (PPP)/kWh, 2.9 billion USD (PPP) (2.85 billion USD (PPP) in our *mixed-device*). Saying that our results are close would however be misleading, because of some differences between the studies:

1. The size and nature of the sample, as well as its geographical distribution: 80% of the websites sampled in Pearce (2020) are from the United States, compared to our 23%.
2. The geographical location from which the experiment was conducted: all our samples were gathered in Italy. We assume that the experiment in Pearce (2020) was performed in the United States, where the lack of the GDPR might affect which ads and trackers are executed and, in some cases, lead to different webpages being shown.
3. Our energy values for personal computers are not estimated by time-based equations as in Pearce (2020) but calculated directly from power data gathered by a CPU and GPU power-metering interface.
4. Our study is entirely run on a specific computer, without accounting for the power of the average computer, unlike Pearce (2020).
5. Our study uses a lower daily average Internet time of 3.3 h (6.5 h in Pearce, 2020).

The 1), 2), and 3) are objective methodological differences, so they cannot be easily harmonized. We indirectly addressed 4) in the "Desktop vs laptop" section. 5) means our estimates are actually close to twice as big as the ones in Pearce (2020). This can probably be attributed to 3), to our sample and to the fact that the *mixed-device scenario* we used is not conservative, unlike our more accurate *baseline scenario*. Still, we believe that this (albeit incomplete) compatibility between two studies belonging to different fields confirms that online ads and trackers do negatively affect the environment. It also shows our *mixed-device scenario* to be plausible, if somewhat pessimistic (something we had already taken into consideration).

Another earlier study which determined that web ads cause additional energy consumption is Simons and Pras (2010). Their estimate of power usage by ads (2.5 W) is much lower than ours (6.13 W). This might be attributed to radically different methodologies for browsing the web. It can also be attributed to age-related factors: for some context, in 2010 Adobe Flash was very popular (it is now entirely decommissioned according to Adobe, 2020) and Facebook, which in 2018 owned nearly 20% of the US digital ad market, did not even own an ad exchange (Constine, 2021). Additionally, ad and tracking technology has evolved over a decade, and the same could be said for ad-blocking (uBO was first released in 2014 according to its Github repository).

Finally, the percentage of the total power needed by web pages attributable to ads we determined (14.85%) is very close to the percentage of the total loading time of web pages attributable to ads (15% according to Pourghassemi et al., 2020). Even if in the software world a faster program is not always more energy efficient (Pereira et al., 2017), we believe this relationship to be worthy of mention, especially in light of our comparison with Pearce (2020), a study which did calculations based on page load times.

4.2 | Measurements

We assessed exclusively energy consumption by the CPU and GPU, when other peripherals also consume energy. Since we wanted to establish a software-based reproducible methodology and our goal was a more conservative estimate, we deliberately chose to take the lowest possible realistic measurements.

4.3 | Variability

On average, ad-blocking decreases the conjunct CPU and GPU power usage standard error by roughly 1 W (0.99 W). Despite that, we decided not to incorporate variability into our results. The main reason for this assumption is that our tests showed that uBO reduced power variability even when the browser was idle. We also believe that variability can be attributed to factors whose proper estimation belongs to a different discipline, such as the number of connections established by ads and the type of ads.

4.4 | Allocation

We used time-based allocation. Since most web browsing happens on mobile devices (StatsCounter, 2021b) and smartphone usage shows high variability (Falaki et al., 2010), another study (Pärssinen et al., 2018) preferred traffic-based allocation. Our reasoning for choosing time-based allocation was that our study has a much different focus and methodology than Pärssinen et al. (2018), since it focuses exclusively on the client side. We believe the time data we used to be realistic, since it is based on empirical measurements gathered by SimilarWeb. Finally, a time of less than 10 min a day spent on news websites is very low, in line with our intent of calculating conservative estimates.

4.5 | Desktop versus laptop

Our usage of the term “personal computer” conceptually includes both desktop computers and laptops. We exclusively used a desktop computer in our experiment. There are hints that laptops outsell desktop computers (IDC, 2020) and looking at the thermal design power, (TDP, “the power consumption under the maximum theoretical load” according to Intel, 2019) of the top-selling (according to Fischer, 2020) laptops and desktop CPUs in 2015 and 2020 on Amazon.com shows than desktop CPUs can have a TDP more than four times as high as laptops. We selected a 5-year period for our analysis because a formal study has estimated an average lifetime for computers between 3 and 8 years (Teehan & Kandlikar, 2012). We decided to assume the most conservative approximation. This means that there could be differences in power usage, although it is not clear if they affect marginal power values: if so, our results would need to be scaled down by a factor. The experiment in Simons and Pras (2010), which was performed on four different computers including laptops and desktops, showed a difference between them of less than 1 W. These results give us reason to believe that our estimates might be extended to laptops without much effort, even if much has changed in the computing world in more than a decade.

4.6 | Environmental impacts of mobile devices

Our data for mobile devices is inferred rather than gathered directly from the machine. We conducted our experiment on a desktop computer, browsing the desktop versions of all websites. Mobile websites can be separate from desktop versions (Mozilla, 2021), and this difference could be significant in terms of performance and ads. Additionally, some popular web services (such as Instagram) are often used via their official apps rather than web browsers, which can prevent ad-blocking. Finally, the benchmark we used for our calculations refers to a smartphone (Android Dev Phone 2) from 2009 but a study from a decade later (Ayala et al., 2019) shows similar power values, despite using a phone (Samsung Galaxy Nexus) from 2011. We could not conduct our experiments on Android or iOS phones due to technical and budget constraints, even if technically feasible (Rice & Hay, 2010).

On desktop computers, direct environmental impacts are most prominent during the use phase (Teehan & Kandlikar, 2012). In smartphones (Ercan et al., 2016) and tablets (Clément et al., 2020), the bulk of negative impacts is actually outside the use phase (Cordella et al., 2021) even if it must be noted that the possibility to carry smartphones everywhere allows for more prolonged Internet usage times and, consequently, it is possible that there could be rebound effects, which have already been studied in the context of ICT (Gossart, 2015; Hilty et al., 2006; Plepys, 2002;). Just during the production phase, smartphones can require amounts of energy resources as high as 30—40 times their weight and can generate waste amounting to 200 times their weight (Paiano et al., 2013). Smartphones, unlike desktop computers, have batteries, which are a source of environmental damage (Kang et al., 2013). The carbon footprint of smartphones has increased over the years and has been estimated to have surpassed half of the carbon footprints of all other devices combined (Belkhir & Elmeligi, 2018). For these reasons, even if the direct energy consumption of desktop computers is certainly higher than that of smartphones, it cannot be affirmed that smartphones are greener than desktop computers, especially when taking into consideration the shorter average lifespan of smartphones (3 years according to Wieser & Tröger, 2018) compared to that of desktop computers (3–8 years according to Teehan & Kandlikar, 2012, as above mentioned).

Overall, we believe the lack of mobile-specific factors due to the indirectness of their impacts to be the biggest limitation of our study, and a good starting point for future research.

4.7 | Limitations of the research and other considerations

There are other choices which might be perceived as limitations, although they are unlikely to threaten the validity of this study for reasons we shall explain.

We chose to conduct our experiment using the Chromium web browser since it was the free and open source version of the most popular web browser at that time, Google Chrome (StatsCounter, 2021). As shown by some studies (de Macedo et al., 2020; Greenspector, 2021), web browsers might differ in the way they consume energy. This would, in turn, affect our estimates for energy consumption on mobile devices, which is calculated from a proportion based on the power consumption of Chromium when idling.

We browsed every website for 60 s because in-person supervision of the experiment showed that it was enough time to fully load and show the contents of the pages, as well as any ads. We believe that a larger time window would have brought more variability unrelated to ads, since some news websites automatically refresh themselves at programmed intervals and those operations could trigger energy-intensive operations like autoplaying videos or loading new images. When it comes to our calculations, this means that our estimate for marginal energy consumption is to be considered constant.

We browsed all websites one at a time, without clicking any links. Although this might not be realistic, it is enough for websites to load and show ads. We also cleared all personal data each time we switched from one website to the next. This was done to prevent stateful trackers (Englehardt & Narayanan, 2016) from adapting to our browsing history, which would be made our experiment less reproducible.

We did not take into consideration qualitative aspects of the visited web pages, such as structure, scripting, styling, and network usage (Webkit, 2019) .

From the user side, we did not take into consideration the fact that some mobile users browse websites via official or third-party apps. This can lead to radically different estimates, because apps can be written using native as well as web technologies, with varying results in terms of energy consumption (Huber et al., 2022).

The daily Internet time estimate we used is very conservative. Even for the *computer-only scenario*, a report published by private firms in the social network business shows much higher global average times (WeAreSocial & Hootsuite, 2020). We decided not to use that source because they do not provide access to data but it is worth noting that their estimated average, as well as what has been used in published literature (Pearce, 2020), is almost twice as big as ours in the *computer-only scenario*.

With regard to this issue, it has to be stressed that the COVID-19 pandemic has led many people to stay at home, where they spent more time on the Internet according to Obringer et al. (2021). The same study shows an overall increase by 15—40% of GHG emissions attributable to Internet activities, which, considering an average increase of 27.5%, would translate into yearly electricity consumption and GHG emissions of 0.78 TWh/year and 0.37 $MtCO_2e$/year, respectively, for our *baseline scenario*.

Other than strictly environmental issues, studies using methodologies which also incorporate social effects (such as S-LCA) might be interested in evaluating the negative social effects of online advertising, which might include the loss of privacy caused by online tracking and targeted advertising, compulsive buying, and other phenomena. Likewise, methodologies which incorporate economic effects should take into account the possible loss of revenue caused by either ad-blocking or the adoption of alternative, ad-free business models, and related effects on competition.

Even though we believe the user behavior perspective to be important, we also argue that industry-wide changes to the way online ads are delivered can also lead to a reduction of Internet-generated GHG emissions. Text-based ads are certainly less energy intensive than those which display images and videos. Contextual ads, which do not need any tracking code because they deliver ads related to the contents of the page from which they are shown (Chun et al., 2014), can also lead to savings in GHG emissions. Lastly, offering ad-free versions of websites and apps to a subset of paying users would, ceteris paribus, reduce GHG emissions.

Finally, GNU/Linux, the operating system we used to conduct our experiment, is estimated to be used by less than 2% of web users (StatsCounter, 2021c) at the time of writing. According to the same source, Microsoft Windows is used by the majority of desktop web users (76.42% in January 2021). We do not consider this threatening to our study since all tests were executed ceteris paribus (without launching background apps), web technology is standardized and cross-platform, (Heitkötter et al., 2012) and we focused on marginal measures, which we believe are less affected by OS-specific behaviors than absolute power levels.

5 | CONCLUSIONS

Since the majority of global citizens are Internet users and a sizable portion of websites use ad-based business models, we wanted to assess the environmental impacts (in terms of energy and carbon emissions) of online ads and tracking. To do so, we randomly sampled news websites from all over the world and collected first-hand power data when visiting them with and without an ad-blocker from a desktop computer. Our results indicate that ads and trackers on news websites consume 0.61 TWh of electrical energy every year, which translates to GHG emissions equal to 0.29 $MtCO_2eq$ and collective energy costs of 140 million USD (PPP).

Overall, these considerations suggest for more stringent regulations and policies with regard to both awareness and protection of Internet users and lesser-known environmental issues.

Future research could build a sample of websites belonging to multiple categories. Other research could take into account qualitative factors such as the nature of ads being shown or the structure of the webpages which host them. Further research could estimate the differences in power usage between mobile and desktop versions of the same websites, or those between mobile websites and their app counterparts. Finally, the low individual energy costs attributable to ads and tracking could be compared with the estimated costs of privacy loss caused by extensive tracking.

AUTHOR CONTRIBUTIONS

Fabio Pesari: Conceptualization, methodology, investigation, software and data curation, data validation, writing—original draft preparation. Giovanni Lagioia: Writing—review. Annarita Paiano: Conceptualization, data validation, writing—original draft preparation and supervision.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in Zenodo at https://doi.org/10.5281/zenodo.7333212, reference number 10.5281/zenodo.7333212.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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