Impact of User Interaction Patterns on Website Carbon Emissions Across Industries

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ABSTRACT

With the growing concerns on climate change and increasing use of digital services, understanding their carbon footprint has become paramount. The study models web browsing energy intensity over time and combines it with regional grid carbon intensity data and user traffic to estimate the emissions from different websites. The primary aim is to provide a temporal view, highlighting patterns and offering insights into the environmental impact of digital activities. For users, this research offers an understanding of their individual digital footprints. For service providers, it sheds light on the overall footprint considering their website traffic. A significant outlier identified in the study is the news category, which exhibited markedly higher carbon emissions compared to other website categories.

KEYWORDS

user interaction, carbon emissions, digital services, environmental impact

1 INTRODUCTION

As digital services expand, their environmental impact, particularly in terms of carbon emissions, has become a significant global concern. The ICT sector is one of the fastest-growing contributors to global greenhouse gas emissions, heavily influenced by user interactions on various digital platforms. The proliferation of internet technologies and services has led to a significant increase in data usage and energy consumption. As digital services become integral to daily life, understanding their environmental impact is crucial. This research focuses on analyzing the carbon emissions from user interactions on digital platforms across different sectors: e-commerce, news platforms, university websites, and search engines.

User interactions on these platforms vary widely—from continuous data streaming on news platforms to intermittent data requests on e-commerce sites. These variations influence the energy consumption profiles and carbon emissions of these services. Additionally, the carbon intensity of digital services depends on the underlying energy sources, which vary in carbon intensity across regions and over time. This research aims to examine how specific data transfer over a browsing session and user traffic over time contribute to the carbon emissions of selected digital services, with the goal identifying patterns. By focusing on a sample of popular websites from all four sectors and using tools like Google Chrome Developer Tools for data collection and Google Trends for relative traffic, this study offers insights into the carbon implications of digital consumption behaviours.

Targeted research is needed to examine the temporal patterns of carbon emissions resulting from specific user behaviours and compare these impacts across different digital service types. This analysis is essential for developing effective strategies and technological innovations aimed at reducing the carbon footprint of digital activities.

Research Question. This research seeks to address the following question: "How do aggregated browsing sessions on different digital platforms influence the temporal patterns of carbon emissions for websites, and how do these emissions fluctuate with the availability of renewable energy in the grid mix?" This can be answered with the following sub-questions: (1) "What are the per-visit carbon emissions on the selected digital platforms, across sectors?" (2) "How does the data intensity of browsing sessions on these digital platforms correspond to specific levels of electricity consumption under standard operational conditions?" (3) "How does the availability of renewable energy within the regional grid mix influence the carbon emissions associated with these user interactions at different times of the day, month, or year?" (4) "How does website traffic correlate with the carbon emissions?" By filling existing knowledge gaps, this research will provide actionable insights that could lead to significant reductions in website emissions, aligning digital innovation with environmental sustainability.

2 RELATED WORK

The understanding of the environmental impact of digital services has evolved significantly over the past decade, with an increasing focus on how user interactions contribute to carbon emissions. Initial studies, such as those by Coroama, highlighted the potential for digital solutions ,like internet-based conferences, to reduce greenhouse gas emissions compared to traditional methods, setting a foundation for subsequent research in the ICT sector's energy consumption [3].

Malmodin and Lundén provided a more detailed analysis by examining the energy and carbon footprint of the global ICT sector, emphasizing the scale and impact of various digital services from

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2010 to 2015 [8]. During this period, the Ferreboeuf's report also advocated for reduced digital consumption to mitigate environmental impact [5].

Recent studies have broadened the scope to examine the indirect effects of increasing internet use , discussing the overlooked environmental footprint and projecting significant increases in internet electricity use by 2030 [1, 10]. These insights are crucial for planning the infrastructure and technology development needed to address these challenges.

The impact of specific platforms such as TikTok, Facebook, Netflix, and YouTube on carbon emissions has also been examined, illustrating the significant emissions associated with popular social media and streaming platforms [2].

Recent research by Malmodin and Lundén has advanced our understanding of the energy and carbon emissions associated with the ICT sector. Their study provides a comprehensive assessment of the global ICT sector's environmental impact, focusing on current and future projections of energy use and carbon emissions. It emphasizes the growing contribution of internet traffic to global carbon emissions and underscores the urgent need for sustainable practices and innovations to mitigate these effects [9].

The prevailing literature predominantly adopts a top-down approach to estimating carbon emissions, relying on broad specifications and generalized assumptions. This methodology tends to obscure critical details regarding the principal drivers of these emissions, as averaging processes dilute the granularity of the data. Consequently, key contributors to carbon emissions are often overlooked. There is a significant gap in understanding how user traffic patterns to websites—reflected in the overall data transfer and user activity—impact carbon emissions within their respective sectors. This gap is particularly pronounced when considering the variability of these impacts based on the time of day or year and the corresponding availability of renewable energy within the regional grid mix.

3 RESEARCH METHODOLOGY

This study employs a structured approach to analyze the carbon emissions resulting from user interactions on various digital platforms. The research is focused on the Netherlands, using Dutch grid data and websites targeted at a Dutch audience. Data collection was performed using the University of Twente VPN to ensure consistency. The entire year of 2023 was analyzed on a monthly basis; however, this paper focuses on the month of January for detailed analysis. The methodology involves several key steps: website selection, browsing session simulation, data intensity measurement, website traffic estimation, and carbon emissions calculation.

Figure 1 illustrates the steps undertaken in this analysis. The following sections provide detailed descriptions of the methodologies and tools utilized in this study.

3.1 Website Selection

To comprehensively analyze the carbon emissions of user interactions across various digital platforms, a diverse set of websites are chosen for the categories E-commerce, News, Universities and Search Engines.

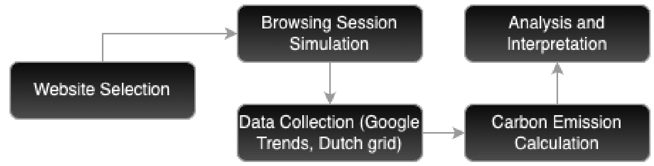

Figure 1: Workflow

For e-commerce, the selected websites represent a broad spectrum of product categories, ensuring a wide coverage of different types of online shopping behaviours. These include Amazon, a globally popular platform offering a wide range of products; Bol.com, a similar comprehensive platform particularly popular in the Netherlands; Zalando, a well-known website focused on clothing; Ikea, a popular furniture retailer with a significant online presence; and Coolblue, a website specialising in electronics.

In the news category, we choose platforms that represent different age demographics and audience interests, including Algemeen Dagblad, De Telegraaf, De Volkskrant, and RTL Nieuws. For university websites, the selection was based on the number of registered students to ensure the data's significance and accuracy, encompassing the University of Amsterdam, Delft University of Technology, University of Groningen, Utrecht University, and Erasmus University Rotterdam.

Due to the limited variety of unique search engines, the most popular and relevant ones for the Dutch audience were selected: Google Chrome, Bing, Yahoo, DuckDuckGo, and Ecosia.

3.2 Browsing Session Simulation

We simulate browsing behaviours for each sector to ensure consistent data collection: **E-commerce**: Five product searches, five product page views, one checkout attempt; **News**: Viewing five articles, watching one video; **Universities**: Searching for five courses, reading five articles, watching one video; **Search Engines**: Performing five different topic searches.

We collect data using the Google Chrome browser on a fresh account, averaged over three sessions to ensure reliability. Each session involved a full page load to capture all elements, conducted via the University of Twente VPN for consistency, with browsing data cleared after each session to avoid caching.

The "data transferred" section within the Network tab of Google Chrome Developer Tools provided a comprehensive overview of all resources loaded, including HTML, CSS, JavaScript, images, media files, web fonts, and dynamic content. The size of each resource included both content size and protocol overhead.

This methodology excludes repeat visitors and cached data to simplify the analysis and eliminate variables that could introduce inconsistencies. Using incognito mode and clearing browsing data ensures each session starts fresh, capturing peak data usage and providing a precise assessment of carbon footprints. This approach avoids unpredictable variables like personalized content and varying session lengths, leading to more reliable results.

3.3 Data Collection

3.3.1 Website traffic.

For each website category, traffic data was downloaded for each month of the year individually using Google Trends. Given that the data over all five websites from each category were gathered in bulk, the traffic was adjusted according to the website with the highest visits.

Google Trends [6] collects and categorizes data from search queries made through Google's platforms, aggregating it to show interest across various geographical levels, from global to city-specific. Using a sampling method, Google Trends processes a statistically representative fraction of total searches.

The search data is normalized by relative popularity, with each data point divided by the total number of searches within the specified geography and time range. Results are scaled from 0 to 100, where 100 represents peak popularity. Low-volume and duplicate searches are included, with low-volume searches appearing as "0." When comparing multiple search terms, the most popular term is scaled to 100, with others scaled relative to it.

Google Trends should be viewed as a reflection of search interest, not as a scientific poll. Increased search volume indicates heightened interest but does not necessarily imply specific website visits. Therefore, Google Trends data should be considered alongside other data points for comprehensive analysis.

In this research, Google Trends data is used for demonstration purposes, illustrating general peaks and curves in search interest over time. Analyzing these trends helps infer patterns in user behaviour and interest. The normalized and scaled data from Google Trends ensures accurate comparisons over time and across different regions, supporting the analysis of carbon emission trends related to web activity in the Netherlands.

3.3.2 Monthly website visits.

To accurately calculate the carbon emissions associated with user interactions on digital platforms, it is essential to estimate the actual monthly website visitors for each selected site. Knowing the number of visitors allows for precise normalization and scaling of data, ensuring that the analysis reflects true traffic volumes rather than relative search interest alone.

For this purpose **Semrush** [11], was employed. It is an online tool used for estimating website monthly visitors, in this research primarily used for data normalization. It employs various methodologies, including traffic analytics and web crawlers, to provide estimates of website traffic. While not a scientific tool, Semrush is effective in distinguishing between websites of varying popularity. Unlike Google Trends, which scales data from 0 to 100, Semrush provides absolute visit counts, offering a more accurate comparison of total visits. This distinction is crucial as it prevents misleading comparisons between websites with similar relative traffic but vastly different absolute traffic levels.

3.3.3 Grid data collection.

To accurately estimate the carbon emissions associated with user interactions on digital platforms, grid data for the Netherlands was collected. This data is essential because it provides daily averages of electricity carbon intensity, a critical aspect of the research that allows for portraying the temporal variations in carbon emissions.

The tool used for this purpose was **Electricity Maps** [4], a platform that provides detailed data on electricity grid operations and carbon intensity. It collects, standardises, and processes data from various public sources such as transmission system operators, balancing entities, and market operators. The platform uses machine learning models to aggregate this data, accounting for power imports and exports between regions. Carbon intensities are calculated by multiplying the electricity consumption from each source by specific emission factors derived from life-cycle analyses.

Analyzing data on an hourly basis poses challenges due to varying user interactions. Focusing on daily interactions over a month maintains granularity and avoids dilution of insights. User browsing habits often follow weekly cycles, influenced by work schedules and leisure activities. By analyzing data over a month, the study captures these patterns, providing a comprehensive understanding of user interactions and their environmental impacts.

3.4 Carbon Emission Calculation

3.4.1 Energy Intensity of data transfer.

CO2.js [12] is widely regarded as an industry standard for estimating the carbon emissions of websites. It is a JavaScript library by the Green Web Foundation, that estimates the carbon emissions of web pages using a lifecycle analysis approach. It considers both embodied emissions from device manufacturing and disposal, and operational emissions from data transfer during page loading. CO2.js takes as input the amount of data transferred in megabytes, including HTML, CSS, JavaScript, images, and other assets, usually gathered with tools like Developer Tools and Google Lighthouse. The library uses standardized energy consumption values for data transfer, derived from studies estimating the average energy required per unit of data.

The model estimates website emissions by combining operational emissions (emissions from data centers, internet networks, and end-user devices) and embodied emissions. The current conversion factors(e) are 0.0194 kWh/GB for operational energy intensity and 0.106 kWh/GB for embodied emissions, based on a global average grid intensity of 494 grams CO2e/kWh. Energy consumption is calculated as follows:

$$\text{E (kWh)} = \text{Data (GB)} \times \text{e} \left(\frac{\text{kWh}}{\text{GB}}\right)$$

However, CO2.js does not align with this research's specific objectives. The reasons include the following: Firstly, the research focuses on operational emissions, which are directly linked to the real-time energy consumption during browsing. Including embodied emissions would overestimate the immediate environmental impact of browsing sessions. Secondly, CO2.js uses static carbon intensity values, which do not account for daily and seasonal variations in the energy grid mix. This research aims to use real-time data to provide a more accurate estimation of temporal carbon emission patterns.

To align with the research objectives, the operational carbon intensity calculation methodology from CO2.js are adapted as follows:

Sources used for the revised methodology include the International Telecommunication Union (ITU) and research by Malmodin,

Table 1: Nomenclature

Symbol	Description
$\overline{V}$	Average daily visits
$\overline{T}$	Average Google Trends value
T_i	Google Trends value on day i
n	Number of days
V_d	Absolute visitors on day d
T_d	Google Trends value on day d
D	Data transferred per session in GB
E_d	Energy intensity on day d
E	kWh per visit
I_d	Carbon intensity on day d
C_d	Carbon emissions on day d

which provide detailed data on operational energy consumption for data centers, networks, and user devices. The total energy consumption is 210 TWh for data centers [9], 247 TWh for the network [9], and 345 TWh for user devices [9]. The total data transfer across the internet is 5.29 ZB[7]. By dividing the energy consumption by the total data transfer, we obtain the energy intensity based on data transfer for each segment: 0.039 kWh/GB for data centers, 0.046 kWh/GB for the network, and 0.065 kWh/GB for user devices. The final value for total operational energy intensity is **0.150 kWh/GB**.

Due to the methodological limitations and the specific requirements of this research, CO2.js is not used in its entirety. Instead, its methodology for calculating operational energy intensity is adapted to align with the research focus on daily browsing emissions and the need for real-time, region-specific data. This approach ensures a comprehensive and accurate analysis of carbon emission trends for websites in the Netherlands.

3.4.2 Normalization and Interpretation.

To derive meaningful insights from the collected data, a systematic methodology was adopted to normalize and interpret the data across different steps. We follow the steps described below:

(1) **Identify the website with the most uniform Google Trends values.**
The key reason for selecting the most evenly distributed traffic site as a reference point is to ensure that the average Google Trends value used for normalization is representative and accurate. Using the average Google Trends value for normalization inherently assumes that the trends data is evenly distributed around the average. This means that the data should not have significant outliers or skewness, as these could distort the average and lead to inaccurate estimates of website visits.

(2) **Calculating Average Daily Visits for the reference website as follows.**

$$\overline{V} = \frac{\text{Total Monthly Visits}}{\text{Days per Month}}$$

(3) **Calculate the Average Google Trends Value for the reference website.**

$$\overline{T} = \frac{\sum T_i}{n}$$

(4) **Normalize the Daily Google Trends Values by the Average Trends Value for the Reference Website and Scale by the Average Daily Visits.**

$$\text{Visits per Trends Point} = \frac{\overline{V}}{\overline{T}}$$

$$V_d = \left(\frac{T_d}{\overline{T}}\right) \times \overline{V}$$

(5) **Calculate the Energy Intensity of a Browsing Session.**

$$E_d = D \times 0.150\,\text{kWh/GB}$$

(6) **Plot Carbon Emission Curve.** Calculate the daily carbon emissions and plot a curve showing the emission trends for the website's browsing activities as follows.

$$C_d = V_d \times E \times I_d$$

Potential limitations

The methodology assumes a linear relationship between the Google Trends traffic values and the actual website visits. This method assumes that the average Google Trends value is a reliable representative of average daily visits. Google Trends data might only provide a relative measure of interest and not absolute visit counts. Extrapolating absolute visit counts from relative trends data relies on the assumption that the trends data accurately reflects user behaviour.

The calculation assumes a constant energy usage per visit. In reality, the energy consumption might vary depending on user activities, the type of content accessed, and the efficiency of the web servers and data centers.

The methodology applies a uniform approach across different websites, which might have varying characteristics in terms of visit patterns, server efficiency, and user engagement.

4 RESULTS

4.1 Presentation of Results

The results of this study are presented through a series of plots that visually represent the data. These plots are designed to clearly illustrate the temporal variations and patterns in carbon emissions associated with user interactions on the selected digital platforms. They provide a clear depiction of emissions from both the perspective of individual visits and the total estimated visits. The following sections describe the key findings from the data analysis. The findings are organized into three distinct stages, each providing insights from different perspectives.

4.1.1 Recorded Data and Energy Intensity. In the first stage of our analysis, we compiled the recorded data intensity of a browsing session for each website. This stage is crucial as it provides the foundational data necessary for understanding the variations in carbon emissions across different websites. Table 2 summarizes the key metric for each website, the data transferred during a browsing session.

This initial stage of analysis lays the groundwork for the subsequent stages, where we delve deeper into the carbon emissions associated with these browsing sessions, considering both user-specific and industry-wide perspectives.

Table 2: Data intensity of web browsing

Website	Data transferred(MB)
Amazon	35.3
Zalando	16.3
IKEA	30.1
Bol.com	7.9
Coolblue	15.7
NU.nl	17.7
Algemeen Dagblad	27.3
De Telegraaf	82.9
De Volkskrant	28.6
RTL Nieuws	52.4
University of Amsterdam	53.9
TU Delft	7.7
University of Groningen	16.8
Utrecht University	7.7
Erasmus University Rotterdam	6.5
Google Chrome	20.7
Microsoft Bing	18.7
Yahoo	14.2
DuckDuckGo	5.7

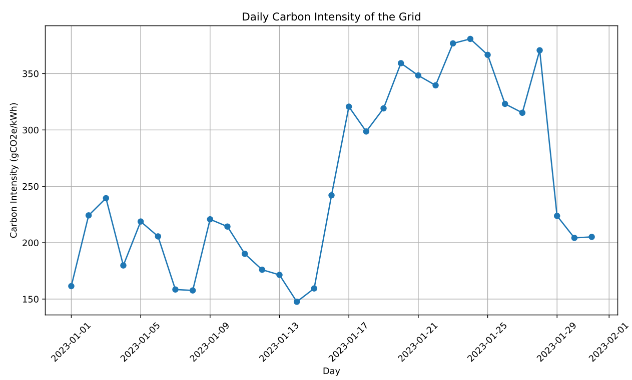

Figure 2: Carbon Intensity of the Dutch grid: January 2023

4.1.2 Carbon Intensity of a Single Browsing Session. In the second stage of our analysis, we examine the carbon intensity of a single browsing session over different days of the month. This analysis provides insights into how daily variations in grid carbon intensity impact the carbon footprint of individual user sessions.

To illustrate our findings, we provide the results for the month of January. Figure 2 illustrates the daily averages of carbon intensity of the Dutch grid over the month of January. These values are used in the plots to calculate the actual emissions of a single website visit by multiplying them by the energy intensity of a browsing session for each website. Figures 3 and 4 illustrate the daily carbon emissions for each of the studied website categories.

4.1.3 Overall Estimated Carbon Emissions. In the third stage of our analysis, we evaluate the overall estimated carbon emissions for the websites over the days of the month. This stage offers an industry perspective, combining grid carbon intensity with actual web traffic data to understand the broader implications of user interactions on carbon emissions.

Figures 5 and 6 present the results from this stage. Figure 5 displays the daily traffic values of each website category over the

Figure 3: Emissions for a single browsing session over the month of January: E-commerce, News

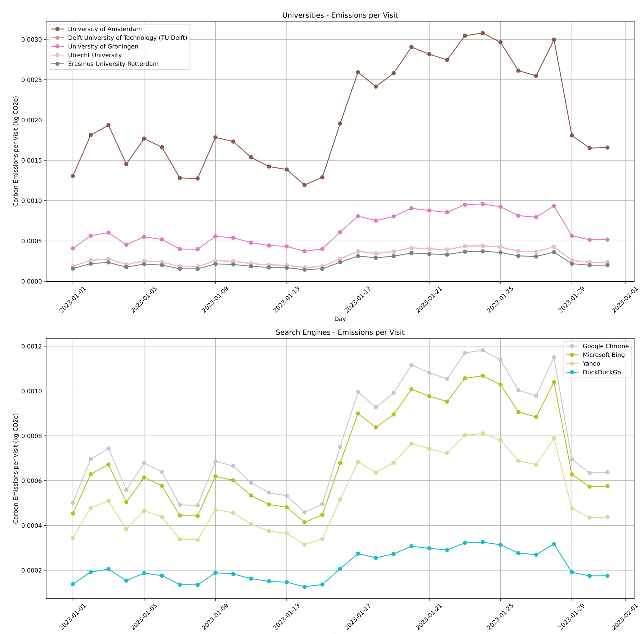

Figure 4: Emissions for a single browsing session over the month of January: Universities, Search Engines

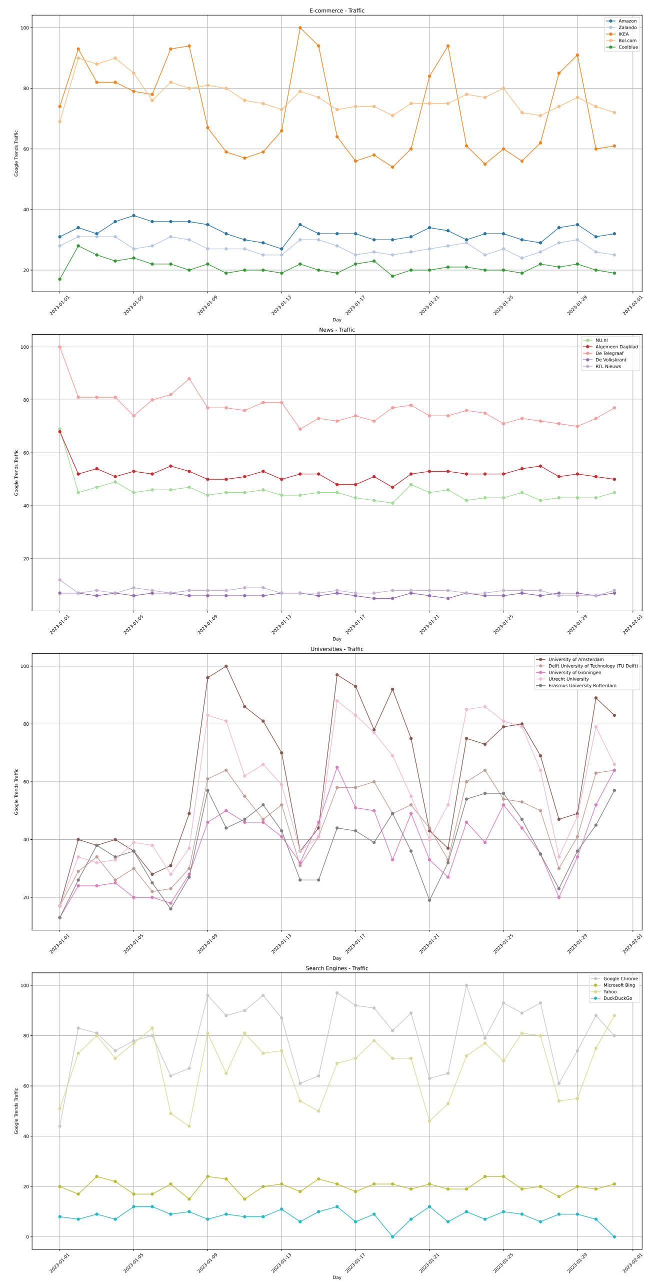

Figure 5: Traffic Values

Figure 6: Carbon Emissions

month of January using Google Trends data. Figure 6 shows the actual aggregated carbon emissions of the websites across the studied categories, providing the corresponding estimated carbon emissions for the given websites.

We have to note that in the last two stages of the data analysis, the scales of the plots are different. Both within each stage (intra-stage) and between the stages (inter-stage), the scales vary. This is because the aggregated website emissions are essentially the single website visit emissions multiplied by the number of visits, which differ significantly. Additionally, the News category exhibits magnitudes higher carbon emissions compared to the other categories. If the same scale were used for all plots, the News category would dominate, causing the emissions data for the other categories to lose all informative detail and their respective curves to flatten. By adjusting the scales, we ensure that each category's unique emission patterns and temporal variations are clearly visible and accurately represented, allowing for a more comprehensive analysis of the data.

4.2 Analysis

In this section, we delve deeper into the implications of our findings on carbon emissions from web interactions. We analyze the significance of the variations observed across different website categories and traffic patterns. The following analyses covers four months: January, April, July, and October. This time-frame allows us to capture seasonal variations and provide a comprehensive view of the carbon emissions associated with user interactions on digital platforms.

4.2.1 Carbon Emissions Per Website Visit.

E-commerce. Amazon and IKEA consistently show the highest carbon emissions due to their significant data transfer volumes, reflecting the fluctuations in grid carbon intensity. Bol.com and Coolblue exhibit lower emissions, indicating efficient data management practices.

News. De Telegraaf consistently has the highest emissions, driven by rich media content and high user engagement. NU.nl and Algemeen Dagblad show moderate emissions, with trends consistent across all months, influenced by grid carbon intensity variations.

Universities. The University of Amsterdam and Delft University of Technology (TU Delft) consistently show higher emissions, likely due to extensive media content. Utrecht University and Erasmus University Rotterdam maintain lower emissions. These trends remain stable across the months, reflecting daily grid carbon intensity fluctuations.

Search Engines. Google Chrome and Microsoft Bing show higher emissions due to extensive data transfer, while DuckDuckGo and Yahoo exhibit lower emissions due to simpler interfaces. These patterns persist throughout the year, significantly impacted by grid carbon intensity variations.

4.2.2 Overall Carbon Emission Estimations per Industry.

E-commerce. Amazon and IKEA consistently exhibit the highest carbon emissions, closely following their traffic peaks as shown by Google Trends. The emissions are significantly influenced by fluctuations in grid carbon intensity. Bol.com and Coolblue maintain lower emissions, indicating more efficient data handling practices.

News. De Telegraaf consistently shows the highest carbon emissions, reflecting its high user engagement and rich media content. NU.nl and Algemeen Dagblad exhibit moderate emissions. The trends in emissions closely mirror the variations in web traffic and grid carbon intensity.

Universities. The University of Amsterdam and Delft University of Technology (TU Delft) consistently show higher emissions compared to other universities. These patterns are influenced by the significant traffic peaks and extensive media content. Utrecht University and Erasmus University Rotterdam maintain lower emissions, reflecting their more efficient data usage.

Search Engines. Google Chrome and Microsoft Bing show higher emissions, correlating with their higher traffic volumes. DuckDuckGo and Yahoo consistently exhibit lower emissions, due to simpler interfaces and efficient data handling. These trends remain stable across all months, impacted by daily and seasonal variations in grid carbon intensity.

4.2.3 Comparaison with CO2.js.

To highlight the importance of this research and provide context to our findings, we compare our results with those obtained using CO2.js, focusing on the E-commerce category. This comparison allows us to see the industry point of reference and appreciate the detailed temporal analysis of emissions provided by our study. We compare our results with those obtained using the Website Carbon Calculator [13], which employs the CO2.js library. This tool is commonly used by individuals seeking to understand the carbon emissions associated with websites. Using the Website Carbon Calculator, we assessed the carbon emissions of the five E-commerce websites. To compare our findings with those of the Website Carbon Calculator, we analyzed our range of per-visit carbon emissions for January 2023 against their specific values. The websites are listed below in ascending order of peak carbon intensity.

Website Carbon Calculator Values			Results from this paper		
1	Coolblue	0.43g	1	Bol	0.25-0.40g
2	Zalando	0.45g	2	Coolblue	0.30-0.85g
3	Bol	0.69g	3	Zalando	0.35-0.90g
4	Ikea	0.74g	4	Ikea	0.75-1.75g
5	Amazon	1.05g	5	Amazon	0.80-2.0g

Table 3: Comparison of carbon intensity values from Website Carbon Calculator and this paper.

The comparison between our findings and those obtained from the Website Carbon Calculator using the CO2.js library reveals several interesting insights. While the overall carbon intensity values are somewhat similar, particularly for Ikea and Amazon, which remain the most carbon-intensive websites within our range, discrepancies exist for Bol, Zalando, and Coolblue.

We investigate these discrepancies by examining the front page load data intensities of the websites, as this is the primary metric CO2.js uses to estimate carbon emissions. Zalando, as expected having a lower front page load data intensity (2.2 MB) compared to Bol (2.9 MB), is less carbon-intensive according to CO2.js methodology. However, Coolblue appears as the least carbon-intensive of all, which contradicts its high front page data intensity (8.2 MB). This is an inconsistency since CO2.js focuses solely on the carbon emissions associated with a single URL it is provided, in this case the front page, rather than a comprehensive browsing session. Upon further investigation, we found that Coolblue yielded the lowest data transfer only in the absence of human intervention, such as not accepting mandatory cookie consent upon the initial page load. In contrast, Zalando and Bol did not require human intervention to load fully, suggesting that CO2.js might not account for scenarios where human actions are necessary for complete data transfer.

4.3 Answering Research Questions

What are the per-visit carbon emissions on the selected digital platforms, across sectors? The study provided per-visit carbon emission estimates for each website category, revealing that e-commerce and news websites generally have higher emissions due to their substantial data transfer volumes, while simpler interfaces like search engines exhibit lower emissions.

How does the data intensity of browsing sessions on these digital platforms correspond to specific levels of electricity consumption under standard operational conditions? Data intensity measurements were conducted using Google Chrome Developer Tools, and these values were used to calculate the corresponding electricity consumption. The results showed a direct correlation between the amount of data transferred and the energy consumed during browsing sessions.

How does the availability of renewable energy within the regional grid mix influence the carbon emissions associated with these user interactions at different times of the day, month, or year? By incorporating real-time grid carbon intensity data from Electricity Maps, the study highlighted how periods with higher renewable energy availability corresponded to lower carbon emissions from web interactions, demonstrating the importance of aligning high-traffic periods with greener grid conditions.

How does website traffic correlate with the carbon emissions? The correlation between website traffic and carbon emissions was established using data from Google Trends and Semrush. The findings indicated that higher traffic volumes lead to increased carbon emissions, emphasizing the need for efficient data management and strategic traffic management to mitigate the environmental impact.

How do aggregated browsing sessions on different digital platforms influence the temporal patterns of carbon emissions for websites, and how do these emissions fluctuate with the availability of renewable energy in the grid mix? By analyzing daily and monthly variations in grid carbon intensity and correlating them with web traffic data, we demonstrated that emissions fluctuate significantly with the availability of renewable energy. The temporal patterns of carbon emissions were highlighted through detailed plots, showing how emissions peak and trough in response to changes in the grid mix.

5 DISCUSSION

Per Visit Analysis. The per-visit analysis highlights significant variations in carbon emissions across different websites. High-traffic websites with rich media content, such as Amazon and IKEA in the E-commerce category and De Telegraaf in the News category, consistently exhibit the highest emissions. Conversely, websites with simpler interfaces and efficient data handling, such as Bol.com, Coolblue, DuckDuckGo, and Yahoo, show lower emissions. These findings emphasize the importance of optimizing web design and data management practices to reduce carbon footprints on a per-visit basis.

Industry Perspective Analysis. The industry-wide analysis further underscores the significant impact of web traffic and grid carbon intensity on overall emissions. Websites with higher traffic volumes, such as Amazon, IKEA, and De Telegraaf, consistently show higher overall emissions. The University of Amsterdam and Delft University of Technology (TU Delft) also exhibit higher emissions due to their extensive media content. This analysis highlights the broader implications of user interactions on carbon emissions and the potential for significant reductions through strategic traffic management and consideration of grid carbon intensity variations.

Combining the findings from both analyses, several key insights emerge: (1) **High-traffic and rich media content websites contribute significantly to carbon emissions**: Websites like Amazon, IKEA, and De Telegraaf consistently show high emissions due to substantial data transfer volumes and user engagement. (2) **Efficient data management and simpler interfaces can reduce emissions**: Websites such as Bol.com, Coolblue, DuckDuckGo, and Yahoo demonstrate lower emissions, emphasizing the benefits of optimized web design and efficient data handling. (3) **Grid carbon intensity variations significantly impact emissions**: Both per-visit and overall emissions analyses show that fluctuations in grid carbon intensity play a crucial role in determining the carbon footprint of web interactions. (4) **Strategic traffic management can achieve emission reductions**: Aligning web traffic with periods of lower grid carbon intensity offers a viable strategy for reducing carbon emissions across all website categories.

Shortcomings of CO2.js Methodology. Based on our investigation of comparing our results with those of CO2.js, we hypothesize that there are shortcomings in the CO2.js methodology that our research addresses. CO2.js operates as an automated algorithm that might not guarantee accurate results in all scenarios. The necessity of human intervention for certain websites means that CO2.js might provide incorrect data if it cannot simulate these interactions. Additionally, CO2.js primarily focuses on the emissions from the front page or a single URL. To estimate the total emissions from browsing, one would need to supply each visited URL individually. This approach can lead to skewed results due to factors unknown to the user, such as the ratio of new vs. returning visitors and the chosen model (whether it includes only operational emissions or both operational and embodied emissions). By addressing these limitations, our study provides a more comprehensive and accurate analysis of carbon emissions, considering real-time user interactions and region-specific data, thus offering a more reliable representation of the environmental impact of digital activities.

6 CONCLUSIONS

This study provides a detailed analysis of the carbon emissions associated with user interactions on digital platforms, specifically focusing on e-commerce, news, university, and search engine websites. Our findings reveal significant temporal variations in emissions influenced by the availability of renewable energy in the grid mix. High-traffic, rich media content websites exhibit higher emissions, while simpler interfaces demonstrate lower emissions. By comparing our results with those of CO2.js, we highlight the importance of real-time, region-specific data for more accurate emission estimations. These insights emphasize the need for optimized web design, efficient data handling, and strategic traffic management to reduce the carbon footprint of digital activities, contributing to broader climate change mitigation efforts.

7 STATEMENT ON THE USE OF AI

During the preparation of this work, the author used ChatGPT for rephrasing parts of the text for improved readability. The author reviewed and edited the content as needed and takes full responsibility for the work.

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