Impact of Users' Behavior on Digital Service Energy Consumption

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***Abstract*—Energy consumption in the realm of ICT is raising concerns, challenging the prospect of achieving net-zero emissions. ICT solutions are seen as efficient and low-cost, yet their impacts leave notable footprints. The high demand for digital services, such as online shopping, is contributing to the increased energy consumption of digital infrastructure. Energy consumption in the digital domain is largely attributed to the hardware and software capabilities and the infrastructure that supports them, while users and their behavioral influences on this consumption are overlooked. However, users are the drivers that power these services; their behavior and usage patterns translate to the energy used by both the software and hardware components. In this context, we investigate the impact of user behavior on the energy consumption of digital services, as effective and efficient technology alone might not provide sufficient change in achieving the desired net-zero emissions. To explore the impact of user behavior on the energy consumption of digital services, we use online shopping as a case study. The objective is to understand how diverse user interactions within the online shopping domain influence client-side and server-side energy usage. To this end, we deployed a mixed research methodology, combining theoretical and empirical analysis, and found significant differences in the energy impact of different users' actions. Our results show that product browsing and product filtering are the user actions with significant energy impact on the server side.**

***Index Terms*—User behavior, Energy Impact, Sustainable Computing, Digital Services, Net zero emission**

I. Introduction

Our society is increasingly digital, marked by interconnectivity and technological advancement. Its sustainability, however, is a concern. We expect that society will require users to be mindful about their digital services consumption; the increase in digital-services demand leads to an unsustainable rise in the energy consumption within the computing continuum, i.e. compute resources that cut across the cloud data center, edge computing systems, and end devices [1]. Given the complexity of this digital age, where all our actions carry environmental implications, it becomes necessary to address the reality of our collective impact. But understanding this collective impact requires transparency, to effectively inform consumers about the implications of their actions on the energy consumption of digital infrastructure.

To achieve the much-talked-about net zero CO_2 emission [2], [3], service users might even need to review their habits. Since the final decisions on which service to consume and how to interact lie with the users, their behaviors and decisions are likely to determine the industry's impact. Prior work profiles energy consumption at the system or application level, this study is among the first to isolate and compare the energy impact of specific, user-initiated shopping interactions using an open, replicable reference application.

A. Problem Statement

The surge in digital services has led to extensive research into their environmental consequences, particularly concerning the energy consumption of electronic communication networks, devices, data centers, and ICT, as highlighted in the work of Guegan and Orgerie [4], Ahvar et al. [5], Ramboll et al. [6] and Kamiya et al. [7]. ARCEP [8] emphasized the importance of measuring energy consumption accurately, as accurate measurement serves as the initial step towards reduction. In 2024, the International Energy Agency (IEA) [9] investigated the magnitude of energy consumption associated with digital technology, and reported an estimated rise in global electricity to 3.4% expected annual growth through 2026, and the global data center energy consumption is estimated to reach 1000 TWh by 2026 (equivalent to Japan's yearly energy consumption). This accelerated rise in energy consumption can be attributed to the proliferation of digital services.

Despite the ubiquity of digital services and their profound impact on daily life, a gap exists in understanding how users' behavior influences energy demand in the computing continuum. As users navigate this digital landscape, their behaviors play a vital role in shaping the trajectory of energy consumption and environmental impacts.

In the landscape of online shopping, where convenience converges with consumerism, sustainability implications loom. Collective action and systemic change are needed to realize the full potential of digital innovations in fostering sustainability.

B. Objectives of the Study

Motivated by the need to address the sustainability of the ICT sector, this study aims to determine how user behaviors and interactions affect energy consumption within the digital infrastructure in the context of digital services. Using online shopping as an example of a digital service, deployed within the computing continuum, we aim to analyze

the relationship between users' behavior and energy impact, identify opportunities for optimizing energy use, reducing carbon emissions, and fostering sustainable digital practices. We intend to achieve these objectives through theoretical and empirical research, and data-driven analysis. We formulated the following research questions to guide us in the research:

RQ1: Does the energy consumption of digital services vary across the different components of the computing continuum?

To answer this question, we propose an empirical study to assess which layer of the continuum has the highest impact on energy within the context of online shopping.

RQ2: To what extent do different user shopping behaviors such as product browsing, cart updates, and product filtering differ in their impact on energy usage?

These research questions guide us in understanding the environmental impact of online shopping. The rest of this paper is organized as follows: Section II discusses the related work, Section III outlines the experimental setup and implementation procedures, Section IV presents our findings, and Section V concludes the paper.

II. Related work

Existing studies have shown efforts made to improve energy efficiency, from optimization of server utilization and renewable energy usage to advanced cooling technologies. Research by Beloglazov et al. [10] extensively examined energy consumption across the cloud layer. Their research identifies that high performance and fulfillment of service level agreements have been the sole aim of data centers. This service level agreement has mostly been fulfilled without considering its impact on energy consumption. Aldossary [11] identifies the energy overhead associated with resource provisioning in cloud data centers. However, these studies often focus on a specific component of the computing continuum overlooking the end-to-end energy consumption. Guegan and Orgerie [4] showed that IoT devices consume little energy individually, but their impact grows with their ubiquity and the infrastructure they rely on. We aim to analyze how energy consumption of digital services impacts the computing continuum in the context of online shopping while accounting for the impact of user behavior. Baneshi et al. [12]used the iFogSim simulator to characterize per-application energy in a multi-application edge/cloud environment, showing that this can guide device placement and improve energy efficiency, and later proposed an energy labeling method for digital services in the computing continuum [13]. While their work is simulation-based, ours measures how user behavior affects energy consumption on end-user devices and servers.

Studies have shown that edge computing reduces latency and energy consumption by processing data closer to the source. Research by Shi et al. [14] and Li et al. [15] shows the energy savings capabilities of edge computing in terms of reduced data transmission rate. Pérez et al. [16] and Xu et al. [17] have researched optimization strategies for energy-efficient edge computing.

At the user device layer, a medium via which digital services are being accessed is known to consume a significant amount of energy, contributing to the carbon footprint of this ecosystem. Preist et al. [18], and Roth and McKenney [19], in their research on the energy consumption of consumer electronics found that end-user's devices take up a greater portion of household energy use. While analyzing energy consumption in mobile devices, Carroll and Heiser [20] and Preist et al. [18], recommend energy-efficient hardware design as a technique for reducing the energy consumption. Cuervo et al. [21] and Ullah et al. [22], discussed the use of effective application offloading techniques as a means of saving energy. Aside, from optimizing hardware and effective offloading techniques, there is a need to understand how user behavior impacts the energy usage of these devices. This behavioral impact is what we intend to understand in the course of this research.

Research by Hinton et al. [23] and Baliga et al. [24] state the importance of considering the entire service delivery chain in energy assessments. However, Tiwari and Khan [25] note that measuring energy consumption across the computing continuum is challenging due to hardware and software variability. Cardoso [26] notes that quantifying the energy use of digital services like a video game is a tremendous challenge because of different heterogeneous platforms and heavy dependence on user behavior.

Several methodologies exist for measuring the end-to-end energy consumption of digital services across the computing continuum. Energy profiling approaches use software tools to track energy consumption. Simulation and modeling methods construct virtual prototypes to imitate the computing environment, as demonstrated by [12] iFogSim approach. Analytical methods rely on empirical models and measured data to estimate consumption, as seen in end-to-end estimation studies for IoT applications [4]. In this study, we adopt an empirical energy-profiling approach, using PowerMetrics to measure process-level energy impact, as detailed in Section III. However, each of these methodologies has its advantages and disadvantages; as such, trade-offs should be considered before a methodology is deployed.

Existing research by Rusek [27], Heikkinen [28], Schein et al. [29], Darby [30] all highlights the importance of user behaviors in designing energy-efficient digital services, noting that to understand how energy is consumed the user behaviors and activities need to be understood. However, we acknowledge the research by Huckebrink [31], which investigates the influence of user behaviors on emissions and costs in residential energy systems, highlighting significant energy savings through simple behavioral changes. Also, Gram-Hanssen [32] compared the roles of efficient technology and user behavior in reducing household energy consumption. The study concludes that both matter, and that without conscious effort from users, even optimized technical solutions may deliver little savings. While studies have explored the impact of user behaviors in the context of smart housing such as Maghsoudi Nia et

TABLE I
GOAL, QUALITY, METRICS FRAMEWORK

Goal, Quality, Metrics framework	
Analyze	the impact of user behavior on online shopping
For the purpose	Evaluating
with respect to	energy consumption and carbon footprint in the online shopping domain
from the perspective	of a user, software developer, and policy maker
in the context of	online shopping in the computing continuum

Table I describes the GQM framework, within the context of the user's behaviors impact on the computing continuum energy usage.

al. [33], there remains a notable gap in understanding how user behaviors shape energy demand across the computing continuum.

III. EXPERIMENT SETUP AND IMPLEMENTATION

This research aims to analyze how user behavior impacts the energy consumption and carbon footprint of digital services in the computing continuum from the perspective of a user, software developer, and business owner within the context of online shopping services. We used the goal, question, and metrics (GQM) proposed by Caldiera and Rombach [34], a framework used to establish a well-structured experimental setup. Guided by the GQM model the research questions were formulated to investigate the methodologies for measuring and the impact of digital services energy consumption in the context of online shopping.

A. Experiment Planning

1) Energy Monitoring Tools: To manage the energy consumption of digital services, we need to know and understand the consumption pattern. For this monitoring tools are required. There is no *one-size-fits-all* tool for energy measurement. In our research we used PowerMetrics [35], a tool designed for macOS. It offers energy impact measurements at the level of granularity of interest (per process) that suits our experiment. Although, the energy impact reported is a composite score without a unit, it gives a detailed insight into how each process and service impacts energy usage.

2) Subject Selection: To effectively assess the energy impact of online shopping behaviors, we chose the Microsoft eShopOncontainers [36], a microservice reference architecture application. The application allows each component to be deployed as a separate service in the same container.

3) Experimental Variables: In answering the proposed research questions, we consider the energy impact score associated with user behaviors as the dependent variable. The independent variables are the user interaction and time.

B. Experimental Hypothesis

The following hypotheses are formulated:

RQ1:

- H_0: There is no variation in the energy consumption of digital services across the different components of the computing continuum.
- H_1: The energy consumption of digital services varies across the different components of the computing continuum.

RQ2:

- H_0 : There is no significant difference in energy consumption among the three primitive shopping actions (product browsing, cart updates, and product filtering).
- H_1: Energy consumption differs significantly among the three primitive shopping actions (product browsing, cart updates, and product filtering).

C. Experimental Design

To assess the variability in users' behaviors' impact on energy consumption in the computing continuum, we chose three primitive actions based on the most frequent tasks performed by online shoppers: product browsing, cart updates, and product filtering. The execution duration for each experiment was set to five minutes, with a cooling time of 1 minute and the experiment was repeated 10 times for each behavior measured to reduce noise.

TABLE II
USER ACTIONS AND GENERATED REQUESTS

Action	Requests generated (Locust task)
Product browsing	GET /, /item, /?type, /cart, /checkout, /user/orders, /?brand
Product filtering	GET /, /item/38, /?brand=10, /item/33, /?type=4, /item/49
Cart update	GET Basket, Basket/update, Basket/modify

Table II summarizes the scripted requests used to represent each primitive user behavior

D. Experiment Setup

The experiment environment was set up on a MacBook Pro, 14-inch 2021. The specification of the experimental devices is shown in Table III. The experiment subject was cloned from the official GitHub repository. It is worth noting that the eShopOncontainers requires a Docker installation for a seamless run. For interaction with the back end, we used a Python script utilizing Locust.io [37] to simulate workload and different numbers of users to measure the energy impact.

We chose the software tool for our measurement because of the granularity in which per-process energy measurements are

TABLE III
TECHNICAL SPECIFICATION OF THE EXPERIMENTAL DEVICE

System Specification	
Parameters	**Specification**
Chip	Apple M1 pro
Memory	32GB
Display	14 inch (3024 *1964)
OS	macOS Sonoma 14.5
Flash storage	994,66 GB
No. of cores	10 (8 performance and 2 efficiency

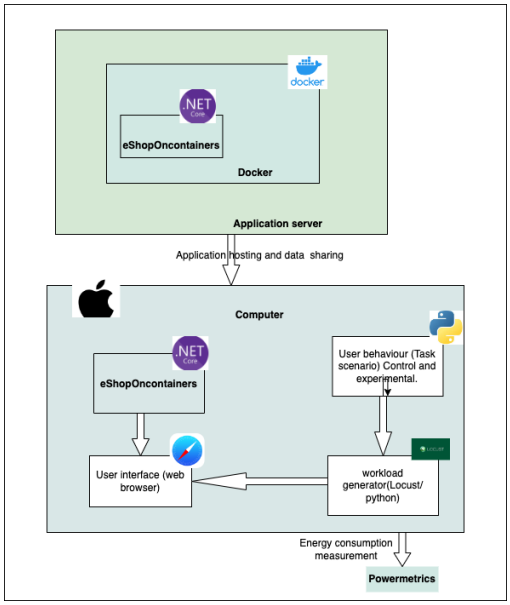

Fig. 1. Experimental setup

given. PowerMetrics can be instrumented to measure specific process energy impact. Although hardware tools are known to be more accurate than software tools, they provide global energy consumption measurement. It is worth noting that software measurement tools are built on empirical estimation, so the energy consumption may vary across different systems as noted by Fahad et. al. [38] in their comparison studies.

E. Data Collection and Analysis

The data for this research was collected using PowerMetrics, while the Locust.io was interacting with the specific service that represents our user behavior of interest. To statistically analyze the data collected during the experiment, we cleaned our dataset and performed basic descriptive statistics and preliminary exploratory analysis. We performed the Kruskal–Wallis test [39], a non-parametric test that compares rankings rather than raw values and is appropriate when the data are not normally distributed. Pairwise comparisons were corrected for multiple testing using the Bonferroni method, which multiplies each p-value by the number of comparisons to reduce the likelihood of false positives. Each behavior group comprised $n = 70$ observations (10 repeated measurements for each behavior).

F. Measurement Procedure

We took a baseline measurement of Safari (the browser from which we access the eShop). We simulated user interactions, product browsing, filtering, and cart updates, and measured the energy impact score. On the client side, isolating this behavior for independent measurement was challenging. On the server side, measurements were collected continuously using the command `powermetrics --samplers tasks --show-process-netstats --show-process-gpu --show-process-energy --show-usage-summary -n 1 -i 5000`, which samples per-process energy impact every 5000 ms (5 seconds). The command ran in the background for the duration of each 5-minute experimental run, yielding 60 samples per run, and was then terminated automatically via a shell script (`kill $PID`). Output was logged with a timestamp to a persistent file.

To support reproducibility, the complete analytical pipeline, experimental scripts, and dataset used in this study are publicly available at [40].

IV. Findings and Discussion

During the exploratory data analysis phase, we discovered that different primitive user behaviors have varying degrees of energy impact on the server. This exploration shows that the energy impacts increase linearly with an increase in the number of concurrent users. However, this linearity gets to an equilibrium after which the energy impact begins to drop. In our experiment, the energy impact progressed linearly upward up to 300 concurrent users. After that point the energy impact begins to drop. Based on our observation, this drop in energy impact resulted from a drop in the number of requests processed and delivered. We deduced that the average number of requests processed and delivered has a direct influence on the energy impact of servers. We also observed that the response time increases with the number of concurrent users, but this rise in the response time did not directly translate to a higher energy impact.

TABLE IV
Descriptive Statistics by User Behavior (Server-Side Energy Impact, Pooled Across Numbers of Users)

Behavior	n	Median	IQR
Product browsing	70	81,239.73	94,960.00
Product filtering	70	61,521.74	98,880.08
Cart update	70	9,471.44	37,727.39

A. User Behaviors and Client-side Energy Impact

We could not isolate specific energy impacts associated with different user's behavior on the client-side. The difficulty in performing a single task without triggering the other behaviors prevented us from gaining insight into how specific behavior impacts energy on the client-side. However, from our measurement, we discovered that for a typical shopping session by a single user for 5 minutes, the energy impact ranges from about 700 - 900. This composite score, which maps hardware resource utilization, indicates that the client-side energy footprint is high [41].

Figure 2 shows the client-side energy impact of a single user interacting with the online shopping platform for 5 minutes. The variation in the energy impact value from the ten experimental runs may be attributed to the fact that the interaction was done manually. The only explanation we can give from this is that each click and scroll has different energy impact associated with them. Since this was manually performed, maintaining the same scroll and clicks for each experimental run is difficult. During this process, we identified

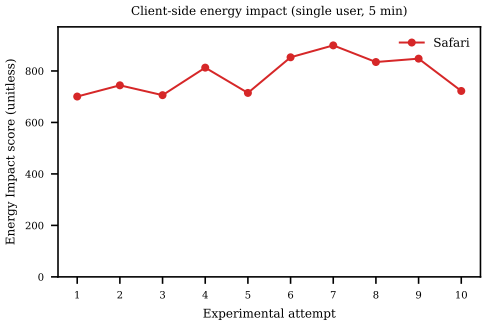

Fig. 2. Client-side Energy Impact

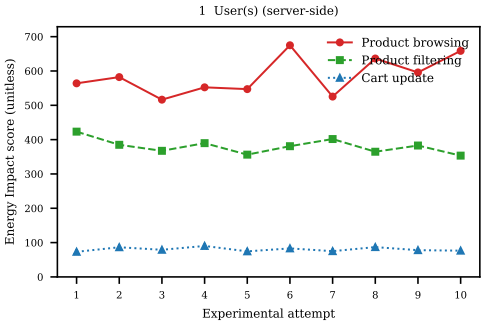

Fig. 3. Single User Energy Impact

browser efficiency as one of the factors that can affect client-side energy consumption. To ensure experimental accuracy, we pre-tested the *"eShopOncontainers"* application alongside three benchmark websites (CNN, live sports, and YouTube) across various browser engines. Consistent with findings by de Macedo et al.. [42], Safari (v17.6) and Google Chrome (v128.0) proved more energy-efficient than Firefox (v127.0) across all scenarios. Because client-side energy footprint is dictated by browser efficiency, Safari was selected as the client-side engine for our study. Challenges encountered during the client-side measurement stem from the energy efficiency of the browser, operating system variation, and the type of device; battery efficiency of the access device and the processor capability also influenced the client-side energy usage. To manage this effect, we ensured that the battery life of our experimental device was between 90 - 100 percent throughout our experiment.

B. User Behavior and Server-side Energy Impact

Next, we measured and analyzed how each user shopping behavior performed by online shoppers on the client-side impacts energy usage on the server-side. We conducted different experiments to account for different numbers of users and different behaviors. On the Server-side, isolating different behaviors and measuring the energy impact associated with them was easy compared to what we noticed on the client-side. This ease came with the utilization of Python script that leveraged *locust.io* to simulate different workloads. This allows for direct interaction with specific behaviors. However, modeling the server-side energy impact of user behavior at scale may be challenging due to the interconnection of different devices. This complexity was controlled because of the simplicity of our experimental setup.

From our analysis on the server-side, as shown in Figure 3, 4, 5 and 6 product browsing and product filtering had the highest energy impact on the server, both higher than cart update across different numbers of users. While the result shows different levels of energy impact on the server due to user behaviors we acknowledge that other parameters such as the frequency of user interaction, and the energy efficiency of the server itself have an impact on energy usage.

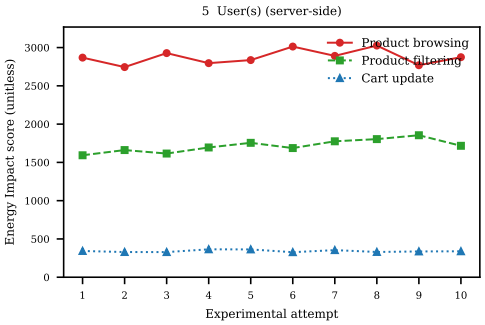

Fig. 4. Energy Impact of 5 concurrent Users

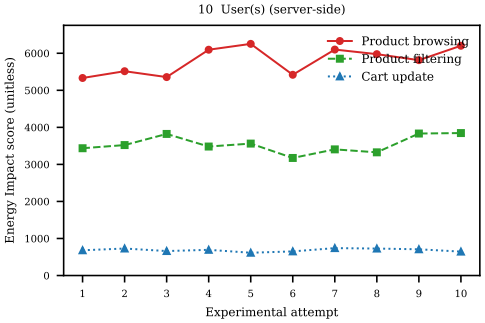

Fig. 5. Energy Impact of 10 concurrent Users

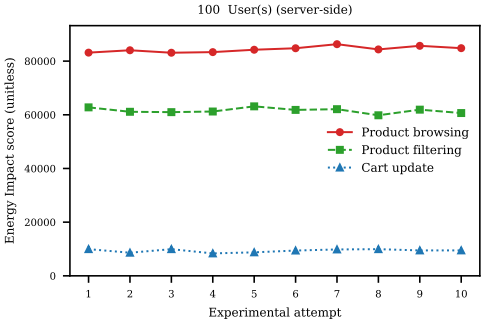

Fig. 6. Energy Impact of 100 concurrent Users

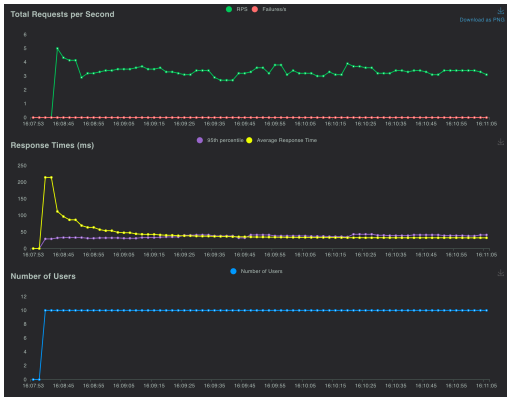

Fig. 7. Request processed and delivered efficiently for 100 users.

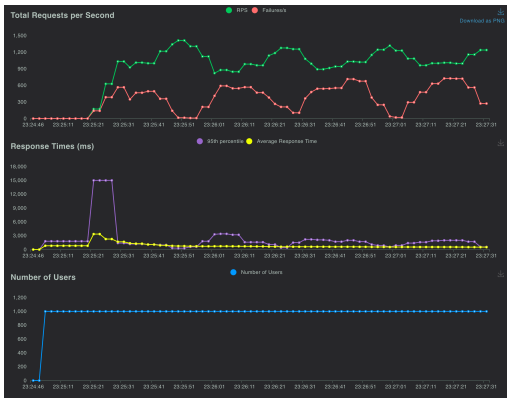

Fig. 8. Decline in request processed as the number of users reaches 1000

To test our hypotheses, we performed descriptive statistics to gain insight into the distribution of our data. We performed Kruskal–Wallis test [39] reporting the chi-square test statistic that shows the difference in ranks of dependent variable "PowerMetrics Energy Impact" across all the independent variables "product browsing, product filtering, and cart updates".

The kruskal chi-square obtained from our statistical test with a p-value of 2.037×10^{-7} is less than the significance level of 0.05. We reject the null hypothesis and accept the alternative hypothesis. We conclude that with 95% confidence there is a significant difference in energy impact across different user behaviors. We further probed to know if the behaviors vary from each other.

TABLE V
PAIRWISE WILCOXON TEST (BONFERRONI-CORRECTED) WITH EFFECT SIZES

Group 1	Group 2	p (adj.)	r	Mag.
Filtering	Cart update	4.2×10^{-6}	0.403	Mod.
Filtering	Browsing	1	0.021	Small
Cart update	Browsing	5.5×10^{-6}	0.408	Mod.

Pairwise comparisons results are reported in Table V. Cart updates differed significantly from both product filtering (($p = 4.2 \times 10^{-6}$), r = 0.403) and product browsing (($p = 5.5 \times 10^{-6}$), r = 0.408), both with moderate effect sizes, while no significant difference was found between product filtering and product browsing (($p = 1$), r = 0.021). These results support the conclusion that cart updates are substantively, less energy-intensive than browsing or filtering, while browsing and filtering themselves are practically indistinguishable in energy impact.

These results address our two research questions. Energy consumption varies meaningfully across layers of the computing continuum: client-side sessions showed a PowerMetrics Energy Impact score of 700 - 900, while server-side scores for individual behaviors ranged from approximately 100 (cart updates) to 600 (product browsing). At the behavioral level, product browsing and product filtering were both more energy-intensive than cart updates on the server side, indicating that database intensive and content-heavy interactions drive energy impact more than state-change interactions. We also found that obtaining single metrics for end-to-end energy usage in the computing continuum is not straightforward based on the insights obtained from our research; existing research supports this due to the inter-connectivity of devices and their heterogeneity at each level of the computing continuum.

C. Mitigating Online Shopping Energy Impact

Based on our research, we propose educating digital service users on the impact of their shopping behavior on the continuum. Frequent shoppers should prioritize the use of energy-efficient devices to access online shopping applications; they should also make use of energy-saving features during online shopping sessions. We suggest that consolidating purchases into fewer, larger shopping sessions may reduce the frequency of energy-intensive browsing and filtering interactions. However, this recommendation addresses only the digital energy footprint measured in this study.

We recommend light web page development for service designers and developers to minimize energy consumption during page loading and rendering. Also, the capability of adaptive web applications that adapt to the user device be explored to reduce the issue of resource contention. Optimizing algorithms that frequently require database access and updates is recommended to reduce energy costs.

V. CONCLUSION, CONTRIBUTION AND FUTURE WORK

The objective of this research was to investigate how user behavior impacts energy consumption in the computing continuum and to propose strategies to mitigate the negative effects of these behaviors. This research is relevant due to the growth in the number of digital services. Understanding how user interaction with these services affects energy usage will help reduce the carbon footprint left behind. Through awareness creation on issues related to sustainability due to digitalization, this research aims to promote environmentally friendly uses of digital solutions.

We presented insights into how different online shopping behaviors affect the energy usage of the computing continuum.

Our results show that product browsing and product filtering have a significant impact on server-side energy, both significantly higher than cart updates. These findings can inform developers about the energy cost of different user interactions and help them decide which parts of their services to optimize. This research provides insights that address a critical aspect of sustainable IT by focusing on user interactions and behavioral patterns.

Besides the behavioral influence of users on energy usage, we identified that browser energy efficiency impacts client-side energy. On the server side, resource contention and saturation, as well as the number of concurrent users and frequency of access, impacts energy usage.

We addressed challenges associated with empirical studies in computer science in terms of energy monitoring and measurement tools, encouraging the design of tools that are cross-platform compatible and suited to new hardware.

This research provides insights into how user interactions during online shopping sessions impact energy usage, which can aid developers in code optimization to reduce resource usage, reduce latency, and improve load balancing. Quantifying the energy impact of different user behaviors highlights behaviors with high energy spikes in online shopping while pointing to where consumption can be reduced to lower carbon emissions. With insights from this research, energy-efficient user behaviors are encouraged. For digital service providers, understanding user behavior can lead to optimization strategies that can be leveraged to reduce energy impact due to user's behavior.

A. Threats to validity

During the research, data collection, and analysis phase, we identified some threats that can influence the validity of our results. These threats cut across, internal, external, and construct validity. User behaviors and technology evolve so these findings might not hold in the future. The experimental results depend highly on the data collected from PowerMetrics, which gives a composite score of energy impact per process. Results may vary with different tools. However, within the setup and technical specification described in Fig. 1, and III this result can be replicated. The accuracy and reliability of tools and methods used to measure energy impact and user behavior may affect the generality of our measurements. Our statistical comparison pools observations across concurrency levels spanning several orders of magnitude; the resulting significance reflects a broad behavioral effect across different load conditions.

Also, operating a client and server on the same device poses both advantages and implications to the experiment. The issue of resource contention will arise due to the computational resources being shared. This contention is capable of elevating the amount of energy used as well as impacting the battery life of the experimental device. To mitigate this threat, we ensured that only the setup needed for the experiment was running. Also, we allowed for cooling time between the experiments to reduce the thermal effect.

On the brighter side consolidating the client and server on a single machine tends to reduce the energy footprint associated with network communication and idle states. On the client side, accurately defining and measuring specific user behaviors was challenging, which could lead to misinterpretation of user actions.

B. Future Work

This research provides a foundation for future studies exploring the impact of user behavior on new technologies' energy usage. Building on our findings, future work will separate the client and server into different hosts to isolate client-side behavior, automate client-side browser interactions to reduce variability from manual clicks and scrolls, incorporate a calibrated physical energy measurement alongside the PowerMetrics proxy score; and replicate this study on additional online shopping applications, device types, and network conditions to test the generalizability of our findings beyond the single configuration examined here.

REFERENCES

[1] AIOTI, "Aioti computing continuum." White paper, 2022. Accessed: April 4, 2024.

[2] European Commission, "Commission proposes new rules on cross-border public services." Press release, Mar. 2024. Accessed: April 4, 2024.

[3] World Bank, "With decisive actions, net zero energy is within reach in the emerging europe and central asia, says new world bank report." Press release, Feb. 2024. Accessed: April 4, 2024.

[4] L. Guegan and A.-C. Orgerie, "Estimating the end-to-end energy consumption of low-bandwidth iot applications for wifi devices," in *2019 IEEE International Conference on Cloud Computing Technology and Science (CloudCom)*, pp. 287–294, IEEE, 2019.

[5] E. Ahvar, A.-C. Orgerie, and A. Lebre, "Estimating energy consumption of cloud, fog, and edge computing infrastructures," *IEEE Transactions on Sustainable Computing*, vol. 7, no. 2, pp. 277–288, 2019.

[6] European Union, "Eurupa dataset," 2023.

[7] G. Kamiya, P. Bertoldi, *et al.*, "Energy consumption in data centres and broadband communication networks in the european union," 2024.

[8] Autorité de régulation des communications électroniques et des postes, "Achieving digital sustainability." https://en.arcep.fr/uploads/tx$_g spublication/achieving-digital-sustainability-report-dec2020.pdf$, 2020.

[9] International Energy Agency, "Electricity 2024: Analysis and forecast to 2026," 2024.

[10] A. Beloglazov, J. Abawajy, and R. Buyya, "Energy-aware resource allocation heuristics for efficient management of data centers for cloud computing," *Future generation computer systems*, vol. 28, no. 5, pp. 755–768, 2012.

[11] M. Aldossary, "A review of dynamic resource management in cloud computing environments.," *Computer Systems Science & Engineering*, vol. 36, no. 3, 2021.

[12] S. Baneshi, A. Pathania, B. Akesson, A. Pimentel, and A.-L. Varbanescu, "Analyzing per-application energy consumption in a multi-application computing continuum," *9th International Conference on Fog and Mobile Edge Computing (FMEC), year=2024*.

[13] S. Baneshi, A. Pathania, B. Akesson, A. Pimentel, and A.-L. Varbanescu, "Empowering sustainability: Energy labeling of digital services using simulation," in *2025 IEEE 25th International Symposium on Cluster, Cloud and Internet Computing (CCGrid)*, pp. 580–585, IEEE, 2025.

[14] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," *IEEE internet of things journal*, vol. 3, no. 5, pp. 637–646, 2016.

[15] Y. Li, A.-C. Orgerie, I. Rodero, B. L. Amersho, M. Parashar, and J.-M. Menaud, "End-to-end energy models for edge cloud-based iot platforms: Application to data stream analysis in iot," *Future Generation Computer Systems*, vol. 87, pp. 667–678, 2018.

[16] S. Pérez, P. Arroba, and J. M. Moya, "Energy-conscious optimization of edge computing through deep reinforcement learning and two-phase immersion cooling," *Future Generation Computer Systems*, vol. 125, pp. 891–907, 2021.
[17] J. Xu, L. Chen, and S. Ren, "Online learning for offloading and autoscaling in energy harvesting mobile edge computing," *IEEE Transactions on Cognitive Communications and Networking*, vol. 3, no. 3, pp. 361–373, 2017.
[18] C. Preist, D. Schien, P. Shabajee, S. Wood, and C. Hodgson, "Analyzing end-to-end energy consumption for digital services," *Computer*, vol. 47, no. 5, pp. 92–95, 2014.
[19] K. W. Roth and K. McKenney, *Energy consumption by consumer electronics in US residences*. TIAX LLC, 2007.
[20] A. Carroll and G. Heiser, "An analysis of power consumption in a smartphone," in *2010 USENIX Annual Technical Conference (USENIX ATC 10)*, 2010.
[21] E. Cuervo, A. Balasubramanian, D.-k. Cho, A. Wolman, S. Saroiu, R. Chandra, and P. Bahl, "Maui: making smartphones last longer with code offload," in *Proceedings of the 8th international conference on Mobile systems, applications, and services*, pp. 49–62, 2010.
[22] I. Ullah, H.-K. Lim, Y.-J. Seok, and Y.-H. Han, "Optimizing task offloading and resource allocation in edge-cloud networks: a drl approach," *Journal of Cloud Computing*, vol. 12, no. 1, p. 112, 2023.
[23] K. Hinton, J. Baliga, M. Feng, R. Ayre, and R. S. Tucker, "Power consumption and energy efficiency in the internet," *IEEE Network*, vol. 25, no. 2, pp. 6–12, 2011.
[24] J. Baliga, R. W. Ayre, K. Hinton, and R. S. Tucker, "Green cloud computing: Balancing energy in processing, storage, and transport," *Proceedings of the IEEE*, vol. 99, no. 1, pp. 149–167, 2010.
[25] K. Tiwari and M. S. Khan, "Sustainability accounting and reporting in the industry 4.0," *Journal of cleaner production*, vol. 258, p. 120783, 2020.
[26] A. Cardoso, "Reducing the energy use of video gaming: energy efficiency and gamification," 2020.
[27] R. Rusek, J. M. Frigola, and J. C. Llinas, "Influence of user behavior on energy consumption and its relation with comfort. a case study based on sensor and crowd-sensed data," 2021.
[28] M. V. Heikkinen, J. K. Nurminen, T. Smura, and H. Hämmäinen, "Energy efficiency of mobile handsets: Measuring user attitudes and behavior," *Telematics and Informatics*, vol. 29, no. 4, pp. 387–399, 2012.
[29] D. Schien, P. Shabajee, M. Yearworth, and C. Preist, "Modeling and assessing variability in energy consumption during the use stage of online multimedia services," *Journal of Industrial Ecology*, vol. 17, no. 6, pp. 800–813, 2013.
[30] S. Darby, "The effectiveness of feedback on energy consumption," 2006.
[31] D. Huckebrink, J. Finke, and V. Bertsch, "How user behaviour affects emissions and costs in residential energy systems—the impacts of clothing and thermal comfort," *Environmental Research Communications*, vol. 5, no. 11, p. 115009, 2023.
[32] K. Gram-Hanssen, "Efficient technologies or user behaviour, which is the more important when reducing households' energy consumption?," *Energy Efficiency*, vol. 6, no. 3, pp. 447–457, 2013.
[33] E. Maghsoudi Nia, Q. K. Qian, and H. J. Visscher, "Analysis of occupant behaviours in energy efficiency retrofitting projects," *Land*, vol. 11, no. 11, p. 1944, 2022.
[34] V. R. B. G. Caldiera and H. D. Rombach, "The goal question metric approach," *Encyclopedia of software engineering*, pp. 528–532, 1994.
[35] Mozilla Developer Network, "Firefox source docs: Power metrics," 2024. Accessed: 2024-08-01.
[36] .NET Foundation, "eshoponcontainers," 2024. Accessed: 2024-08-01.
[37] Locust.io, "An open source load testing tool." https://locust.io/.
[38] M. Fahad, A. Shahid, R. R. Manumachu, and A. Lastovetsky, "A comparative study of methods for measurement of energy of computing," *Energies*, vol. 12, no. 11, p. 2204, 2019.
[39] W. H. Kruskal and W. A. Wallis, "Use of ranks in one-criterion variance analysis," *Journal of the American Statistical Association*, vol. 47, no. 260, pp. 583–621, 1952.
[40] N. O. Bassey, "User-behavior-impact-of-digital-services: Replication package," 2024. https://github.com/nsybee/User-behavior-impact-of-digital-services.
[41] Apple Inc., "Measuring energy impact and performance in xcode," 2023.
[42] J. de Macedo, J. Aloísio, N. Gonçalves, R. Pereira, and J. Saraiva, "Energy wars-chrome vs. firefox: Which browser is more energy efficient?," in *Proceedings of the 35th IEEE/ACM International Conference on Automated Software Engineering*, pp. 159–165, 2020.