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# 6G-SORUS

## SORUS-RIS-A2.1-E2

### "Experiment Design and Development"

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GOBIERNO  
DE ESPAÑA

MINISTERIO  
DE ASUNTOS ECONÓMICOS  
Y TRANSFORMACIÓN DIGITAL

SECRETARÍA DE ESTADO  
DE TELECOMUNICACIONES  
E INFRAESTRUCTURAS DIGITALES



Plan de Recuperación,  
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## Disclaimer

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## Resumen ejecutivo

En el ámbito de las telecomunicaciones, comprender el consumo de energía de los teléfonos inteligentes es un área crítica de enfoque. Con aproximadamente 8 mil millones de teléfonos inteligentes en uso a nivel mundial, examinar cómo estos dispositivos consumen energía durante el uso de internet puede resaltar oportunidades para mejoras y optimizaciones significativas. A pesar de su importancia, esta área sigue siendo relativamente inexplorada por los investigadores.

Nuestro objetivo es identificar los factores principales que contribuyen al aumento del consumo de energía en los teléfonos inteligentes durante el uso de internet. Para lograr esto, nos hemos concentrado en elementos clave como el tamaño del contenido, las tecnologías de acceso radioeléctrico (3G, 4G, 5G, WiFi), la antigüedad del dispositivo (modelos más nuevos vs. más antiguos), los operadores de redes móviles (por ejemplo, Vodafone, Movistar) y los tipos de aplicaciones (navegadores web, redes sociales, transmisión de video). Al identificar estos factores, buscamos descubrir conocimientos que puedan impulsar un uso más eficiente de la energía en los teléfonos inteligentes.

## Abstract

In the telecommunications landscape, understanding smartphone power consumption is a critical area of focus. With approximately 8 billion smartphones in use globally, examining how these devices consume energy during internet usage can highlight opportunities for significant enhancements and optimizations. Despite its importance, this area remains relatively underexplored by researchers.

Our objective is to identify the primary factors contributing to increased energy consumption in smartphones during internet usage. To achieve this, we have concentrated on key elements such as content size, radio access technologies (3G, 4G, 5G, WiFi), device age (newer vs. older models), mobile network operators (e.g., Vodafone, Movistar), and types of applications (e.g., web browsers, social media, video streaming). By pinpointing these factors, we aim to uncover insights that can drive more efficient energy use in smartphones.



## 1. Introduction

In the era of advanced wireless communication, understanding the energy consumption of user devices across various network environments is critical. With the advent of 5G technology, it becomes imperative to evaluate how this new network standard impacts the power consumption of end-user devices compared to previous technologies such as 4G, 3G, and WiFi. This report presents the design and development of a software framework aimed at collecting energy metrics from user devices, specifically focusing on smartphones operating across these different radio access technologies (RATs).

The primary objective of this task is to measure the energy footprint of mobile devices while performing typical tasks on various popular applications. Instead of focusing on network-based measurements, we connected the devices to a power monitoring tool to directly measure power consumption during common usage scenarios. For web browsing, for example, we measured the power consumption when navigating to websites of different sizes, studying the impact of the RAT, web browser (such as Firefox or Chrome), and the website itself. This analysis assesses the relationship between these variables and power consumption.

To ensure consistency and accuracy in our measurements, we used MacroDroid (Arlosoft, 2012), an automation tool, to simulate user behavior across all types of applications. This included web browsing, social media, and video streaming apps. For instance, in the case of social media apps like TikTok, MacroDroid was used to automate user actions such as scrolling through videos for 60 seconds, providing a standardized method for measuring power consumption across different scenarios. In the case of video streaming, we present only the methodology for measurement and some initial results in terms of power consumption; more experiments and detailed results per RAT will be presented in the final deliverable.

For this study, we used two smartphone devices, the Google Pixel 4 and Google Pixel 5, to conduct experiments. We examined the energy usage of the most popular web browsing apps, several social media applications, and popular video streaming services. These applications were evaluated under different radio access technologies (3G, 4G, 5G) as well as WiFi, to measure the power consumption in each scenario. The results provide insights into the energy efficiency of different applications and network connections, contributing to a better understanding of how emerging technologies like 5G can impact overall device power consumption.

This report details the methodology, execution, and findings of these experiments, offering valuable data that can inform future developments in mobile technology and network infrastructure.

## 2. Measurement methodology

In our methodology, each device operates via a battery bypass system, drawing power directly from two terminals connected to the Monsoon (Monsoon Solutions Inc., 2023) instead of the mobile's device battery. The Monsoon device captures voltage and current data, which is then transmitted to and stored on a Raspberry Pi Model B (Raspberry Pi Ltd, 2019). From there, the data is relayed to a personal laptop for preprocessing and analysis. The Raspberry Pi manages the Monsoon device, ensuring accurate energy consumption data collection from the smartphone and controlling the voltage supplied to the device's terminals to keep the smartphone operational. Figure 1 describes the main hardware and software components used. Overall, some of the content in this section, such as Figures 1 and 3, has been previously introduced in the delivery where the environment for performing energy measurements was described (i.e., deliverable SORUS-RIS-A2.1-E1).

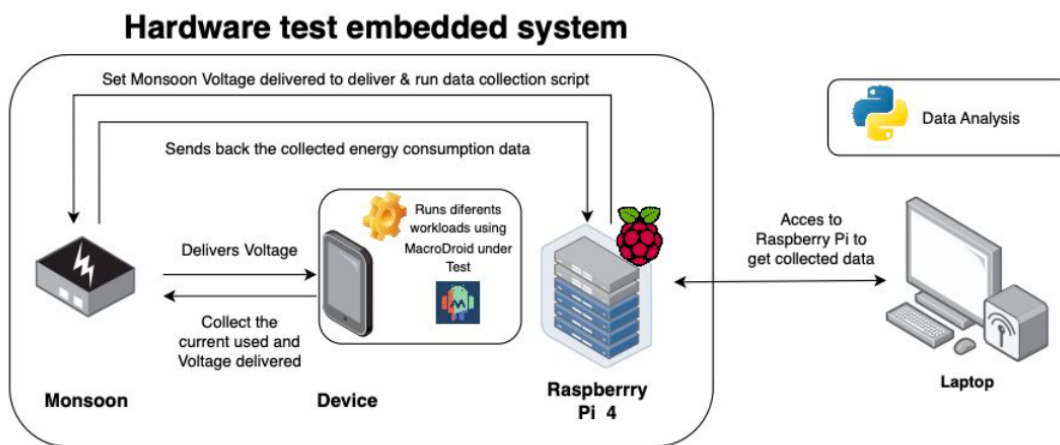


FIGURE 1 Description of the HW/SW testbed used for experimentation

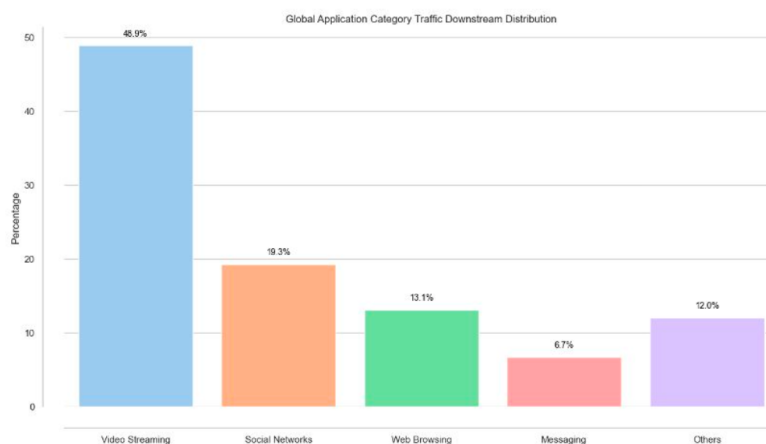
The test duration is predetermined, with data collection beginning simultaneously with the start of each device test. To create a non-intrusive test methodology, we automate the tests locally, avoiding the use of Android ADB (Android, 2023) as ADB connections could potentially impact the smartphone's energy consumption results.

All devices are rooted and running the same Android version, Android 12.0 (Android, 2021). We utilize the MacroDroid application (Arlosoft, 2012) to create macros specific to each test type. These macros automate the interface interactions, streamlining the process of collecting energy consumption data.

For each test type, we have established a series of repetitive actions that mimic normal usage patterns of various applications. During analysis, we define a time window for each test type to calculate the total average power consumption for each use case.

It is important to emphasize that this is a very error-prone activity. Overall, we have conducted 1,437 experiments, but only about 10% (approximately 160) were performed successfully. The other tests encountered issues such as data recording problems, sudden device disconnections (due to the battery bypass system, where small movements could cause the device to turn off), or errors due to the internal behavior of the applications. For instance, with web browsers, we initially overlooked the significant impact of having the cache enabled, leading us to rerun the experiments using private browsing.

To ensure truly representative measurements, we analyzed global mobile traffic data (Sandvine, 2021) and selected three primary application types—video streaming, social networks, and web browsers—which together account for over 80% of total traffic (see Figure 2 for a detailed traffic breakdown). For each application type, we downloaded the most popular alternatives. The specific application names and versions used in our tests are detailed in Table 1.



**FIGURE 2 Popularity of different types of applications**

**TABLE 1 Application name (colour coded by type) and version installed.**

	App	Domain	Version
1	Google Chrome	Browser	118.0.5993.30
2	Firefox	Browser	119.0.1
3	Edge	Browser	118.0.2088.66

4	Brave	Browser	1.60.110
5	Twitter (X)	Social Network	10.23.0
6	Facebook	Social Network	453.0.0.40.107
7	Instagram	Social Network	313.0.0.26.107
8	YouTube Shorts	Streaming	19.07.39
9	Instagram (Reels)	Streaming	313.0.0.26.107
10	TikTok	Streaming	33.2.5

Additionally, to measure the impact of mobile network operators, we selected three of the most popular operators in Spain (Statista, s.f.), namely, Movistar (movistar, s.f.), Vodafone (vodafone, s.f.) and Yoigo (yoigo, s.f.).

## 2.1. Measurement methodology browser applications

To effectively isolate browser trials, we developed a cyclic macro using the MacroDroid app. This macro launches a browser application, loads a web page, waits 20 seconds, and then closes the application and its processes. This procedure consistently runs in 'private mode' to prevent cache accumulation during the trials.

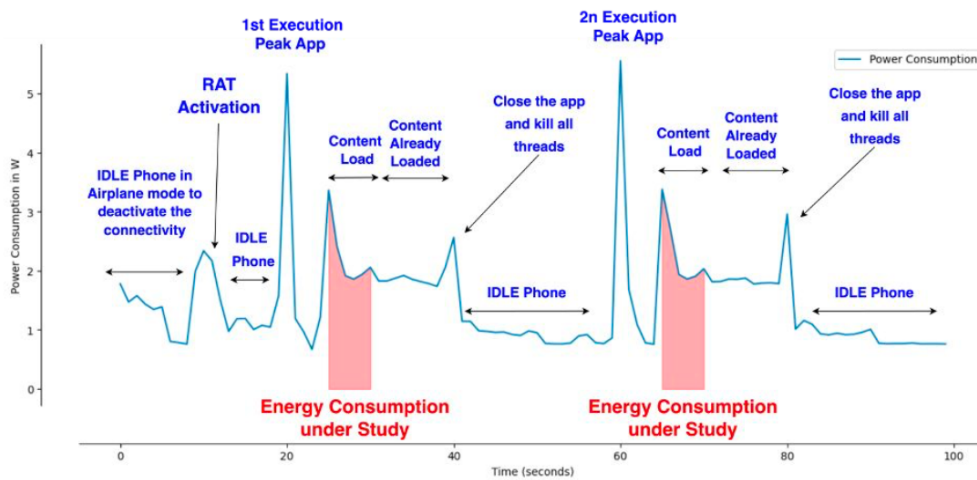


FIGURE 3 Web browsing measurement pattern

Details on the measurement pattern are presented in Figure 3, more broadly, the trial pipeline is defined as follows:

- Device stabilization: The first 25 seconds of each trial are allocated for device stabilization before commencing the measurements.
- Measuring the energy consumption of the test: A 5-second window is used to measure energy consumption immediately after the web page is loaded. Additionally, a 20-second window is used to measure baseline energy consumption when the phone is idle on the main page. This baseline represents the energy consumption of an idle phone on the Android home screen with the corresponding Radio Access Technology (RAT) connected for each test.
- Repetitive actions: For each trial, a loop of 10 identical actions is performed to obtain representative values of the impact of web page loading on the device's energy consumption.

The final energy consumption value is calculated by averaging the values obtained from the measurement window. Figure 4 illustrates the results for 10 consecutive trials, clearly showing a significant increase in Joules consumption during the testing period compared to the baseline period (i.e., when the application is idle).

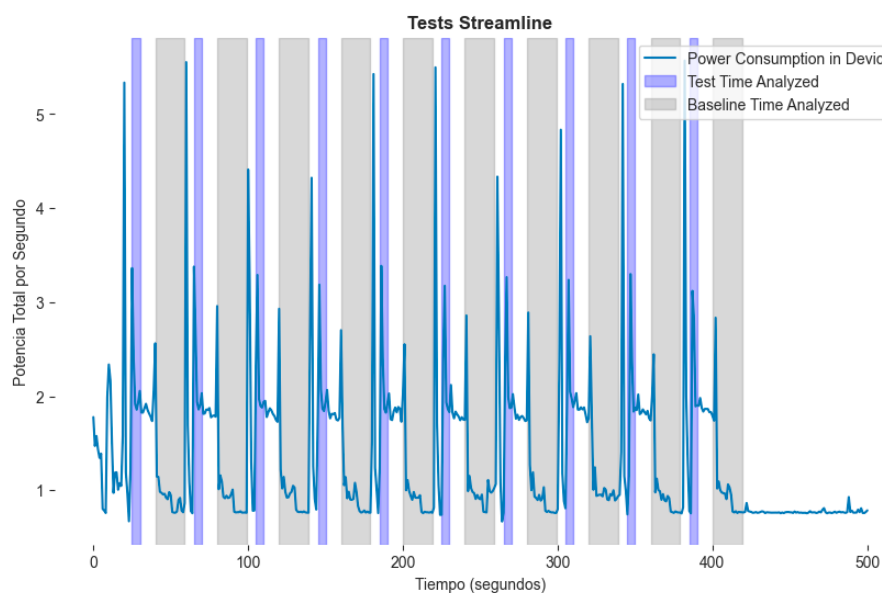


FIGURE 4 Current consumed over test consecutive test

Figure 5 presents the difference in average power consumption between the testing period and the baseline, revealing an increase from 1 to 2.2 Joules on average. The consistency of results across the 10 trials suggests that the tests were conducted correctly. This example pertains to one web page and one browser; a more in-depth analysis is provided in Section 3.

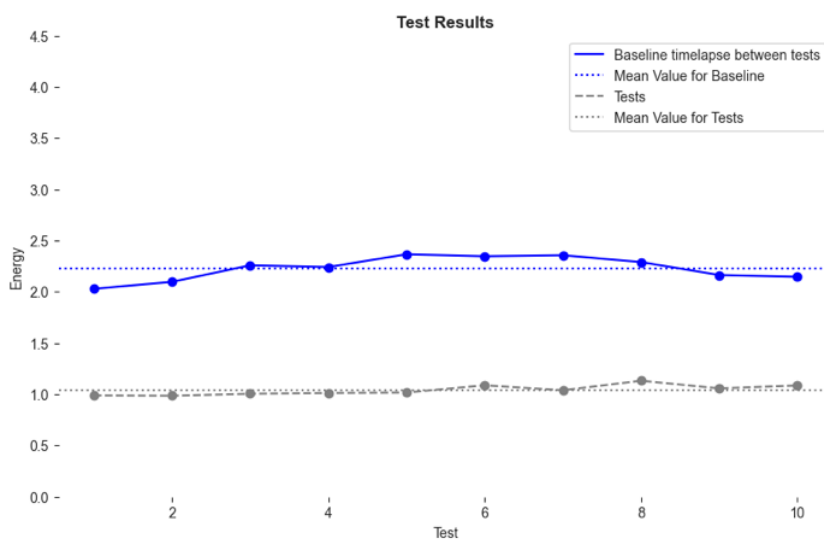


FIGURE 5 Comparison of baseline results against test results

## 2.2. Measurement methodology for social network and video streaming applications

As in the methodology described for web browsers, the approach for measuring power consumption in social network and video streaming applications is outlined in Figure 6. These types of applications generally exhibit more consistent energy consumption patterns. Additionally, Figure 7 demonstrates that both baseline and test period energy consumption for video streaming applications are higher than those for social network applications. A more detailed analysis is provided in Section 4 for social network applications and Section 5 for video streaming applications.

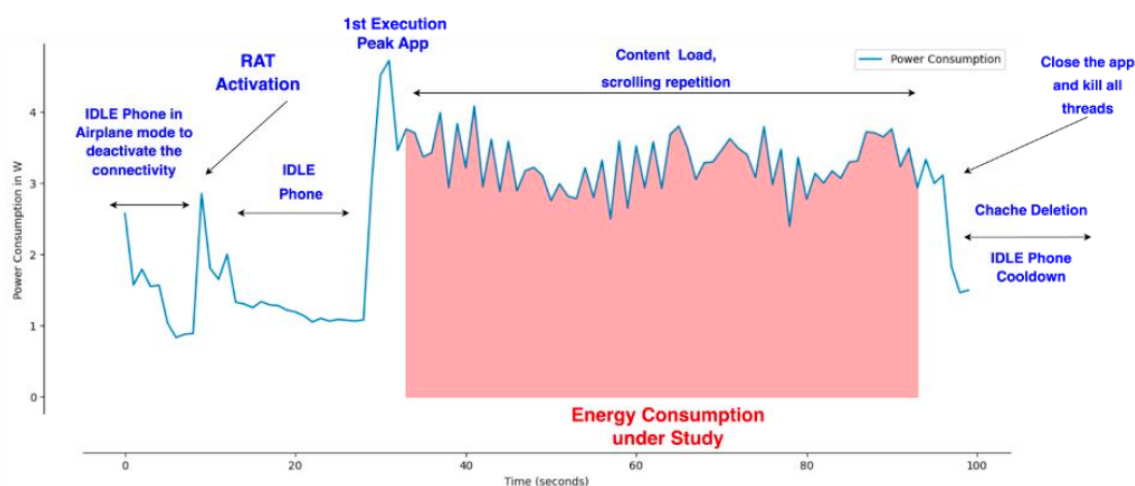


FIGURE 6 Measurement pattern for either social network or video streaming

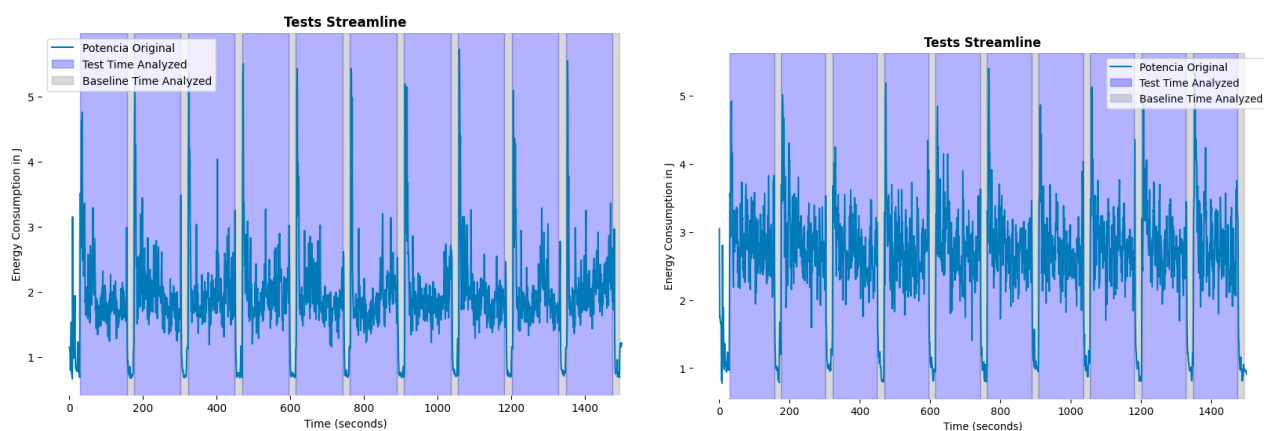


FIGURE 7 ENERGY CONSUMPTION IN JOULES FOR SOCIAL NETWORK APPS (LEFT) AND VIDEO STREAMING APPS (RIGHT)

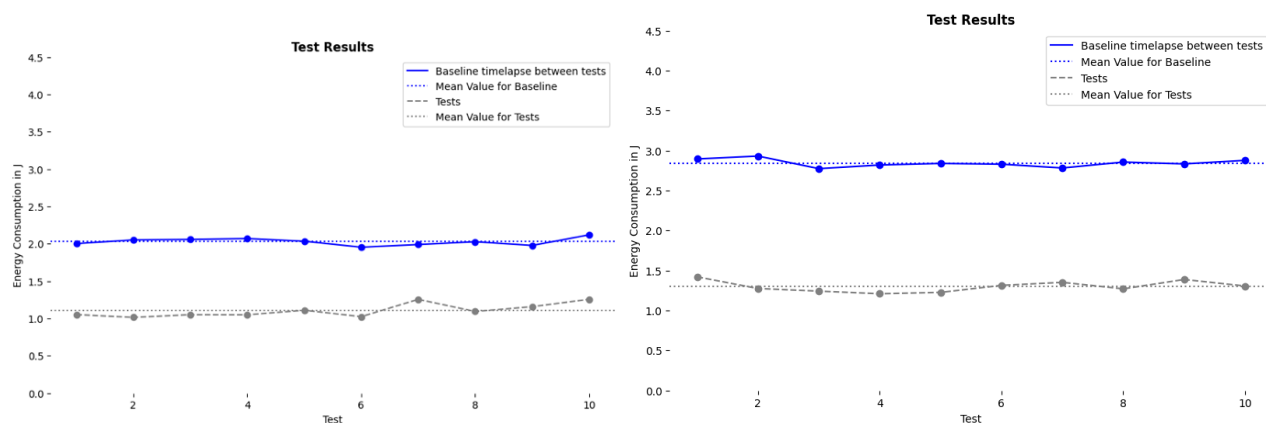


FIGURE 8 BASELINE AND TEST RESULTS FOR SOCIAL NETWORK APPS (LEFT) AND VIDEO STREAMING APPS (RIGHT)



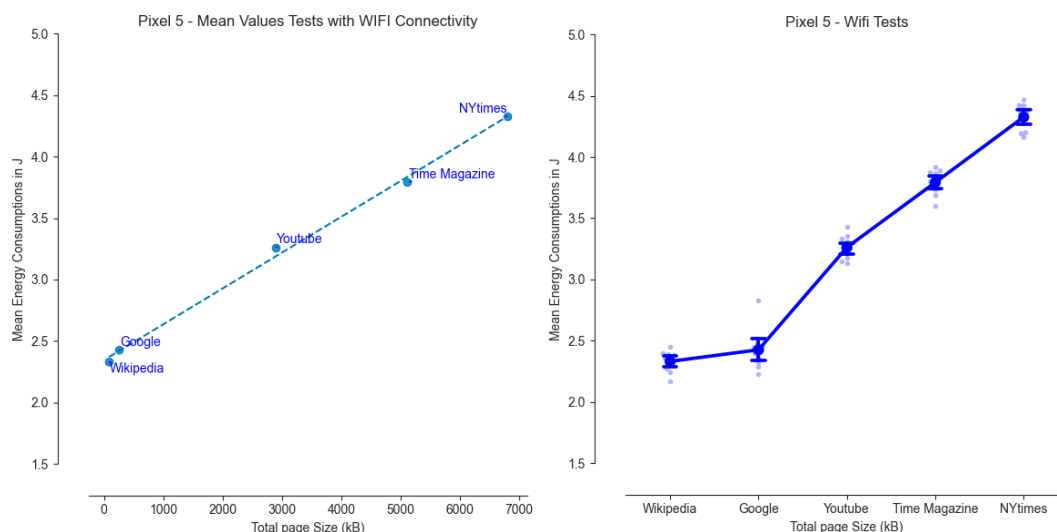
### 3. Effect of website size, RATs and browser type on energy consumption

#### 3.1. Impact of the web page size

A premise from previous work (Narayanan, 2021) is that as the size of a web page increases, the energy required to load the page also increases. To verify this premise, we considered five of the most popular websites: Wikipedia (cite work) namely, Wikipedia (wikipedia, s.f.), Google (google, s.f.), YouTube (youtube, s.f.), Time Magazine (magazine, s.f.), and New York Times (times, s.f.).

The size of the web pages was calculated by inspecting the HTTP Archive (HAR) files, and these measurements were double-checked by analyzing the page sizes through the online service GTMetrix (GTMetrix, s.f.). Figure 9 presents both metrics: the energy consumed to load the websites and the sizes of these websites. As expected, the correlation holds. Moreover, Table 2 presents relevant statistics (mean, standard deviation, etc.).

Initially, we set the connectivity type to WiFi and loaded the five globally popular web pages on the latest available device, the Google Pixel 5, to observe the energy consumption of each web page. We found that the energy consumption difference between the largest web page (New York Times) and the smallest (Wikipedia) is 86.07%.



**FIGURE 9** Energy consumption of loading five popular websites (left); the size of the websites measured daily over one week (right)

TABLE 2 Power consumption using pixel 5 devices, chrome web browser, and connected through WiFi

Webpage	Mean	Median	Standard Deviation	Val. Min.	Q1	Q3	Val. Max
Google	2.4250	2.4178	0.1637	2.2270	2.3376	2.4539	2.8300
Wikipedia	2.3302	2.3544	0.0851	2.1685	2.2771	2.3904	2.4487
YouTube	3.2613	3.2558	0.0961	3.1322	3.1849	3.3248	3.4300
Time Magazine	3.7923	3.7998	0.0997	3.5969	3.7412	3.8698	3.9186
New York Times	4.3267	4.3613	0.1089	4.161	3.7412	3.8698	4.4688

### 3.2. Impact of the RAT

For the second trial, we examined the impact of different Radio Access Technologies (RATs)—specifically 3G, 4G, 5G, and WiFi—on energy consumption to understand the influence of each RAT on the overall average energy consumption. Figure 10 illustrates that, on average for the studied websites, newer RATs are associated with higher energy consumption. Specifically, loading the same website using 4G or 5G instead of 3G results in a 13.24% and 17.56% increase in energy consumption, respectively. Detailed energy consumption data for each of the studied RATs can be found in Tables 3 (3G), 4 (4G), and 5 (5G).

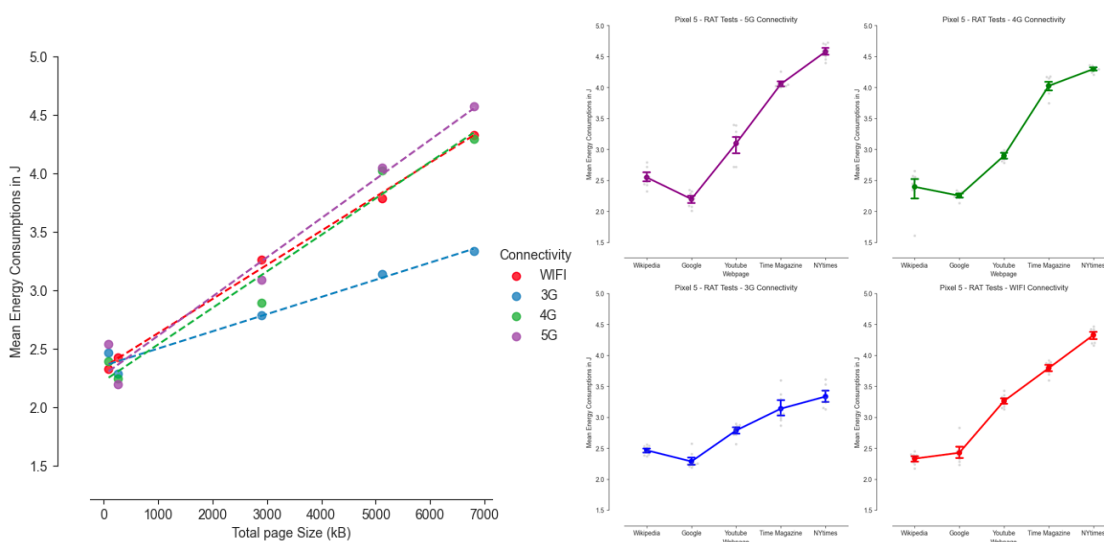


FIGURE 10 ENERGY CONSUMPTION FOR DIFFERENT RATs

**TABLE 3 POWER CONSUMPTION AND SIZE TESTS USING PIXEL 5 AND CHROME AS WEB BROWSER USING 3G – MOVISTAR AS OPERATOR**

Webpage	Mean	Median	Standard Deviation	Val. Min.	Q1	Q3	Val. Max
Google	2.2844	2.2460	0.1189	2.1852	2.2246	2.2625	2.5765
Wikipedia	2.4647	2.4590	0.0677	2.3705	2.4082	2.5242	2.5597
YouTube	2.7859	2.8059	0.0973	2.5681	2.7335	2.8529	2.8959
Time Magazine	3.1372	3.0560	0.2206	2.8683	3.0072	3.2548	3.5949
New York Times	3.3335	3.2865	0.1618	3.1283	3.2391	3.4311	3.6120

**TABLE 4 POWER CONSUMPTION AND SIZE TESTS USING PIXEL 5 AND CHROME AS WEB BROWSER USING 4G – MOVISTAR AS OPERATOR**

Webpage	Mean	Median	Standard Deviation	Val. Min.	Q1	Q3	Val. Max
Google	2.2497	2.2409	0.0599	2.1335	2.2169	2.2991	2.3343
Wikipedia	2.3933	2.4677	0.2952	1.6046	2.3627	2.5488	2.6481
YouTube	2.8959	2.9061	0.0736	2.7840	2.8390	2.9534	2.9899
Time Magazine	4.0250	4.0370	0.1312	3.7482	3.9768	4.1204	4.1785
New York Times	4.2963	4.2900	0.0474	4.2097	4.2799	4.3290	4.3587

**TABLE 5 POWER CONSUMPTION AND SIZE TESTS USING PIXEL 5 AND CHROME AS WEB BROWSER USING 5G – MOVISTAR AS OPERATOR**

Webpage	Mean	Median	Standard Deviation	Val. Min.	Q1	Q3	Val. Max
Google	2.1951	2.2023	0.1101	2.0075	2.1114	2.2752	2.3401
Wikipedia	2.5453	2.5463	0.1398	2.3250	2.4484	2.6105	2.7914
YouTube	3.0948	3.1336	0.2454	2.7156	2.9619	3.2674	3.3933
Time Magazine	4.0534	4.0315	0.0747	3.9991	4.0159	4.0509	4.2572
New York Times	4.5769	4.5783	0.1101	4.3984	4.5130	4.6720	4.7253

### 3.3. Energy consumption under multiple MNOs

We briefly explored whether different Mobile Network Operators (MNOs) impact power consumption values. However, a comprehensive comparison requires measurements at multiple locations, which is not feasible with our current setup. Any small movement automatically turns off the device, making it impossible to conduct tests while moving around the city. Despite this limitation, we performed measurements at a fixed location: Telefonica's Innovation Office in Barcelona (Plaça d'Ernest Lluch i Martin, 5, Sant Martí, 08019 Barcelona). Table 6 shows the signal strength measured from the device.

**TABLE 6 SIGNALLING LEVEL FOR THE DIFFERENT MOBILE NETWORK OPERATORS.**

	Operator	RAT Level	Signal
1	Movistar	3G	58 dBm 62 asu
2		4G	74 dBm 66 asu
3		5G	74 dBm 66 asu
4	Vodafone	3G	74 dBm 46 asu
5		4G	109 dBm 31 asu
6	Yoigo	3G	92 dBm 28 asu
7		4G	87 dBm 33 asu

The results for the Vodafone operator are detailed in Tables 7 and 8, while the results for the Yoigo operator are shown in Tables 9 and 10. Various factors, such as antenna location, connectivity status, and the number of connected devices, influence these results and should be studied further to make any definitive conclusions. However, the current data suggests that the Movistar operator consistently yields lower energy consumption values.

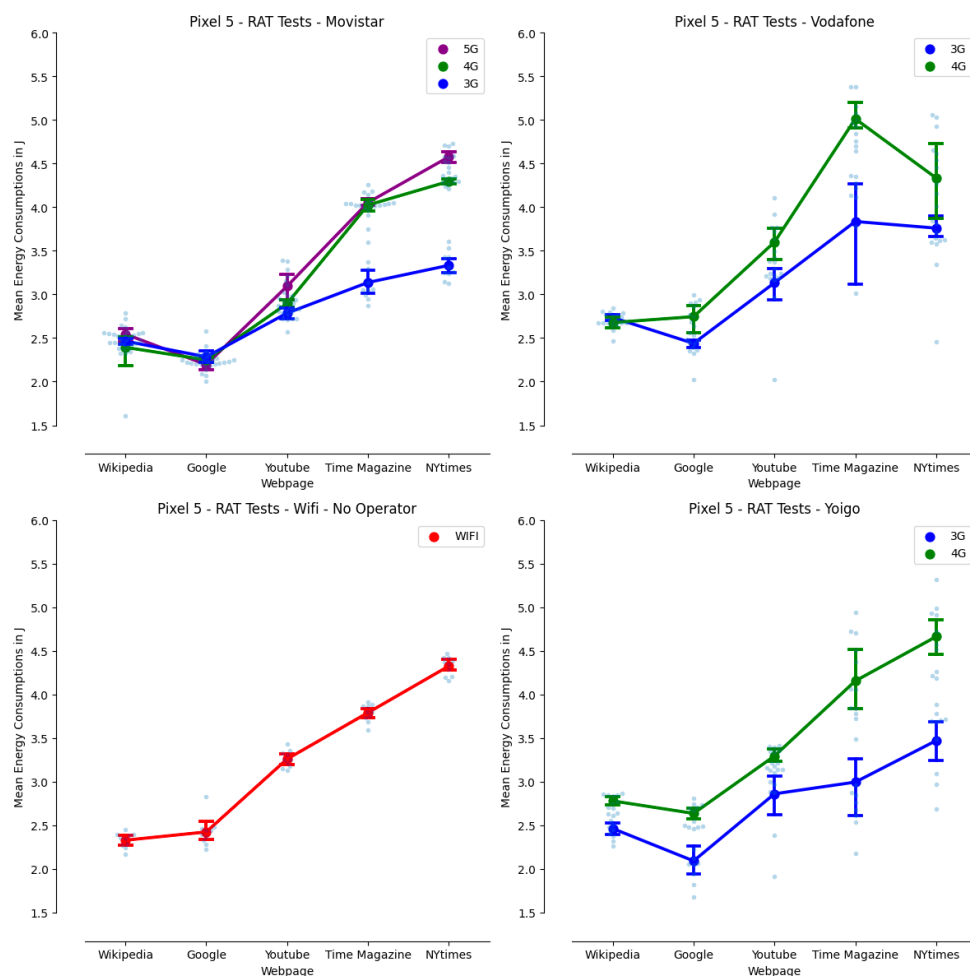


FIGURE 11 Energy consumption on different RATs and different MNOs

TABLE 7 POWER CONSUMPTION AND SIZE TESTS USING PIXEL 5 AND CHROME AS WEB BROWSER USING 3G – VODAFONE AS OPERATOR

Webpage	Mean	Median	Standard Deviation	Val. Min.	Q1	Q3	Val. Max
Google	2.4386	2.4442	0.0779	2.3275	2.3739	2.4861	2.5585
Wikipedia	2.7346	2.7515	0.0666	2.6430	2.6724	2.7689	2.8424
YouTube	3.1336	3.2290	0.3957	2.0264	3.1882	3.2822	3.3775
Time Magazine	3.8363	4.1791	0.9640	1.4118	3.8600	4.3331	4.7041
New York Times	3.7601	3.6761	0.1939	3.5814	3.6205	3.8349	4.1525

TABLE 8 POWER CONSUMPTION AND SIZE TESTS USING PIXEL 5 AND CHROME AS WEB BROWSER USING 4G – VODAFONE AS OPERATOR

Webpage	Mean	Median	Standard Deviation	Val. Min.	Q1	Q3	Val. Max
Google	2.7453	2.8125	0.2785	2.0231	2.7002	2.9053	2.9927
Wikipedia	2.6778	2.6859	0.0970	2.4642	2.6592	2.7207	2.8008
YouTube	3.6000	3.6812	0.3400	2.9639	3.4443	3.7679	4.1059
Time Magazine	5.0130	4.9851	0.2425	4.648	4.8599	5.1333	5.3816
New York Times	4.3348	4.5802	0.8247	2.4548	4.3145	4.8555	5.0568

TABLE 9 POWER CONSUMPTION AND SIZE TESTS USING PIXEL 5 AND CHROME AS WEB BROWSER USING 3G – YOIGO AS OPERATOR

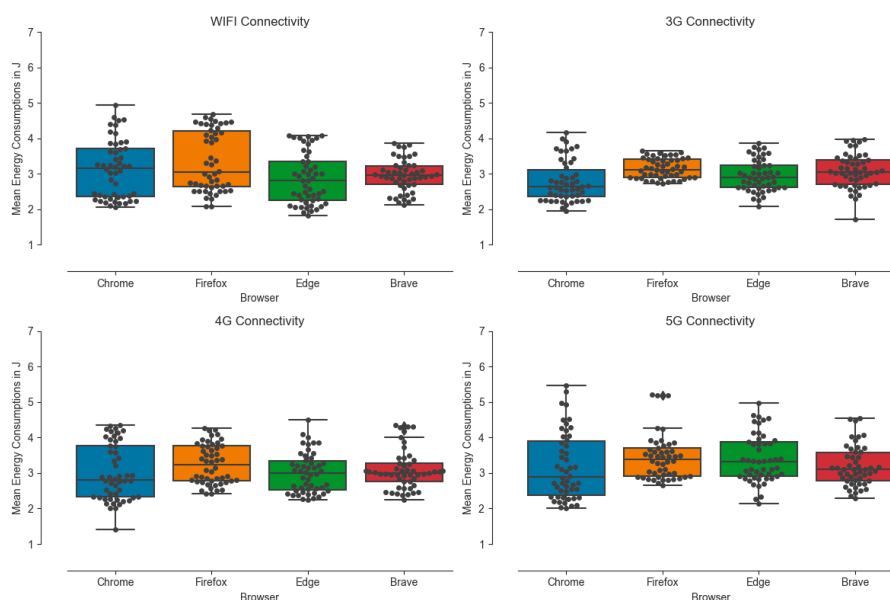
Webpage	Mean	Median	Standard Deviation	Val. Min.	Q1	Q3	Val. Max
Google	2.0926	2.0634	0.2572	1.6777	1.9670	2.2010	2.4862
Wikipedia	2.4643	2.4667	0.1257	2.2609	2.3846	2.5452	2.6396
YouTube	2.8619	2.9833	0.4053	1.9126	2.8816	3.1311	3.1739
Time Magazine	2.9965	2.8210	0.5829	2.1819	2.6299	3.5350	3.8420
New York Times	3.4719	3.6924	0.4057	2.6890	3.1964	3.7147	3.8824

TABLE 10 POWER CONSUMPTION AND SIZE TESTS USING PIXEL 5 AND CHROME AS WEB BROWSER USING 4G – YOIGO AS OPERATOR

Webpage	Mean	Median	Standard Deviation	Val. Min.	Q1	Q3	Val. Max
Google	2.6373	2.6868	0.1248	2.4654	2.5147	2.7252	2.8132
Wikipedia	2.7804	2.8035	0.0857	2.6150	2.7170	2.8489	2.8656
YouTube	3.2961	3.3441	0.1101	3.1281	3.2147	3.3865	3.4174
Time Magazine	4.1563	4.2221	0.6396	2.8467	3.9006	4.6555	4.9394
New York Times	4.6640	4.6509	0.3778	4.1867	4.3283	4.9274	5.3168

### 3.4. Energy consumption for different web browser applications

We conducted the same experiment with four different web browsers: Chrome, Brave, Edge, and Firefox (see figure 12). The energy use for each browser is shown in the following figures and tables. Overall, the differences between browsers are small. However, in our specific setup, Chrome appears to be the most energy-efficient browser, followed by Brave (with a 2.06% increase), then Edge (with a 3.12% increase), and finally, Firefox, which consumes the most power (with a 5.99% increase).



**FIGURE 12 ENERGY CONSUMPTION (IN JOULES) FOR DIFFERENT WEB BROWSER APPLICATIONS UNDER DIFFERENT RATs**

### 3.5. Energy consumption for Pixel 4 vs Pixel 5

Lastly, we examined the energy usage of two smartphone generations: Google Pixel 4 and Google Pixel 5 (see figure 15). We discovered that regardless of the Radio Access Technology (RAT), newer smartphones tend to consume more power than older ones. This is probably because newer smartphones come equipped with more energy-demanding processors. On average, the Pixel 5 smartphone consumes 19.26% more energy than its predecessor, the Pixel 4. Statistical details on the measurements performed are in Table 11.

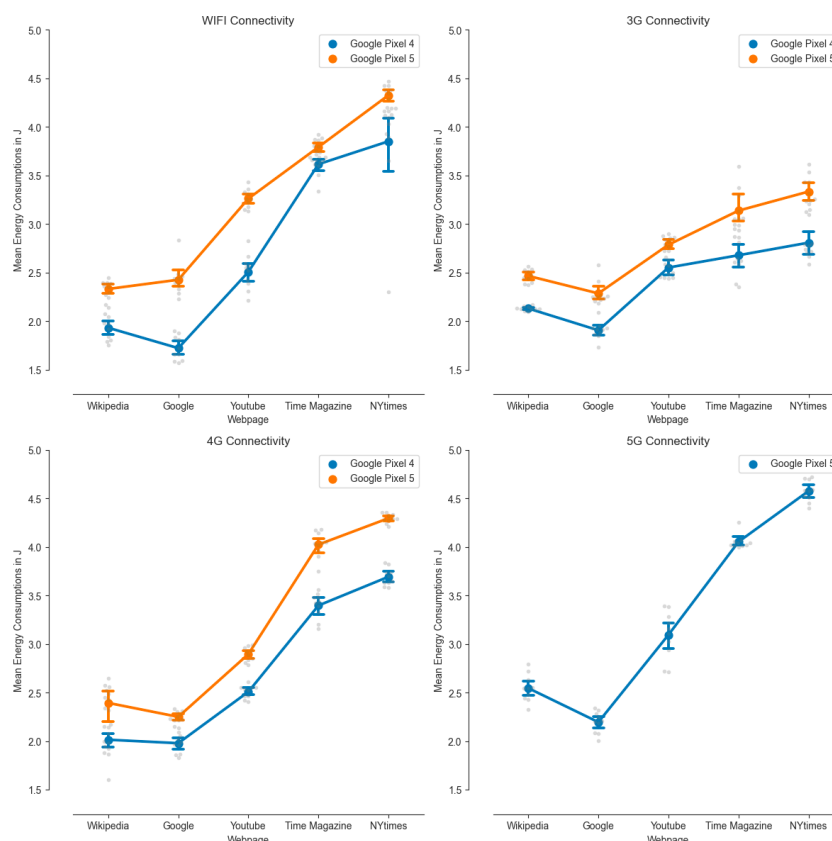


FIGURE 13 POWER CONSUMPTION FOR TWO GENERATION OF SMARTPHONES (PIXEL 5 AND PIXEL 4)

TABLE 11 POWER CONSUMPTION COMPARISON BETWEEN DEVICES USING CHROME AS WEB BROWSER AND DIFFERENT RAT – MOVISTAR AS OPERATOR

Device	Mean	Median	Standard Deviation	Val. Min.	Q1	Q3	Val. Max
Google Pixel 5	2.6189	2.4749	0.7170	1.5723	2.0037	3.2066	4.1944
Google Pixel 4	3.1234	2.9366	0.7891	1.6046	2.4216	3.8923	4.7253

### 3.6. What drives energy consumption the most in the context of web browsers?

In general, considering the conditions outlined earlier, Figure 16 illustrates the factors that have the greatest and least impact on overall energy consumption during web browsing on smartphones.



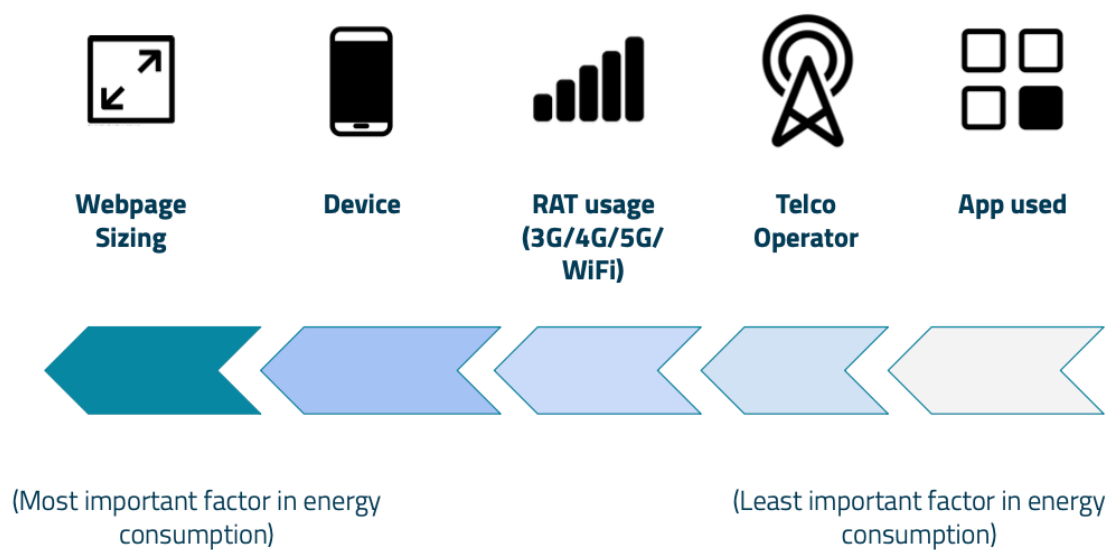


FIGURE 14 IMPORTANCE OF DIFFERENT FACTORS IN THE CONTEXT OF WEB BROWSERS

## 4. Effect of RATs and social networks application on energy consumption

Much like our investigation into web browsers, we aim to identify the primary factors or variables influencing smartphone energy consumption. Specifically, we examine the three most widely used applications: Facebook, Instagram, and Twitter. Given that these apps regularly update content, our initial focus is on understanding the effects of enabling or disabling caching. As depicted in the Figure 17 below, enabling caching indeed decreases energy consumption, aligning with our expectations. However, it is noteworthy that the variability across the three apps is generally minimal on average.

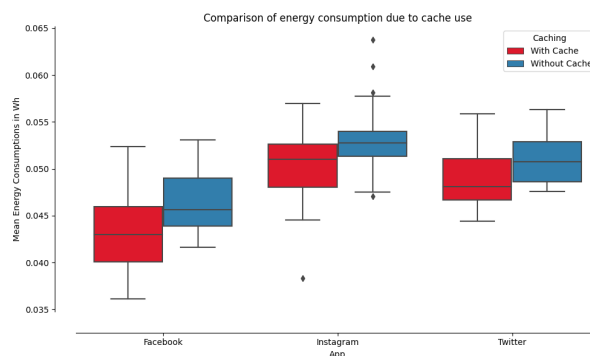
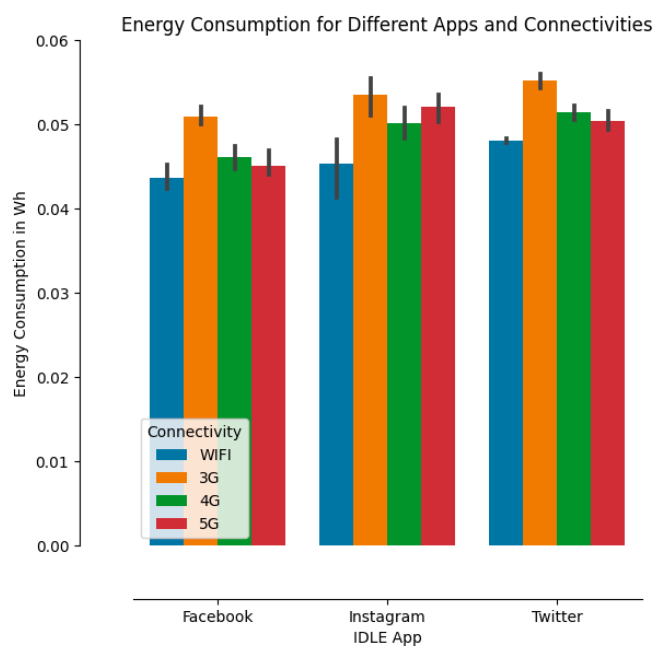


FIGURE 15 ENERGY CONSUMPTION WITH AND WITHOUT CACHE

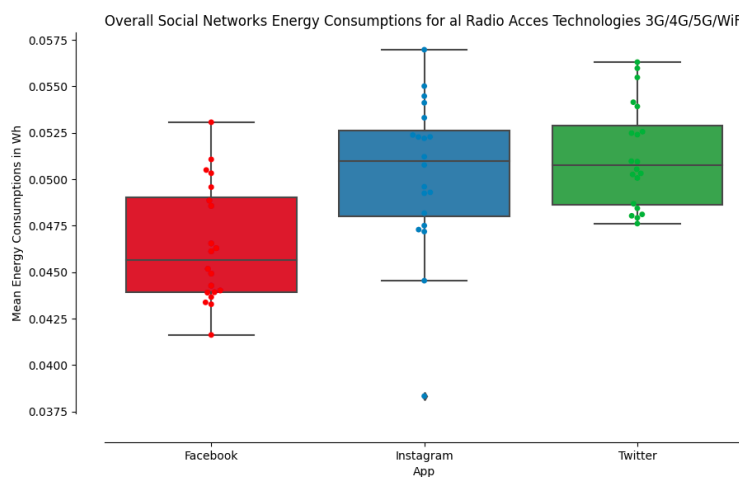
### 4.1. Effect of different RATs

Figures 18 and 19 depict the overall power consumption of the three aforementioned apps across different RATs. One significant finding is that RATs that prove to be most efficient for web browsing do not necessarily maintain the same efficiency when used for social networks. Specifically, WiFi emerges as the most energy-efficient RAT, followed closely by 4G and 5G (which exhibit nearly identical power consumption, with a marginal difference of approximately 0.03%), consuming 7.9% more power. Conversely, 3G stands out as the most power-hungry RAT, consuming 16.44% more energy.

Furthermore, regardless of the RAT, it becomes evident that the Facebook app is the most energy-efficient, while Twitter/X ranks as the least efficient. Moreover, the Instagram app consumes 8.40% more energy than Facebook, and Twitter/X consumes 9.52% more.



**FIGURE 16 ENERGY CONSUMPTION FOR SOCIAL NETWORK APPS ON DIFFERENT RATS. THE ERROR BARS PRESENT THE VARIABILITY OVER 10 INDEPENDENT EXPERIMENTS**



**FIGURE 17 VARIABILITY IN ENERGY CONSUMPTION FROM SOCIAL NETWORKS**

## 4.2. Data consumption for social network apps

With the shift in the order of RATs based on energy consumption, we tried to understand the underlying factor driving this change. We investigated the influence of file size on power consumption across various apps but found no notable correlation (refer to Figure 20 and Figure 19). Despite Instagram's files being, on average, five times larger than those of Twitter, the energy consumption of Twitter exceeds that of Instagram.

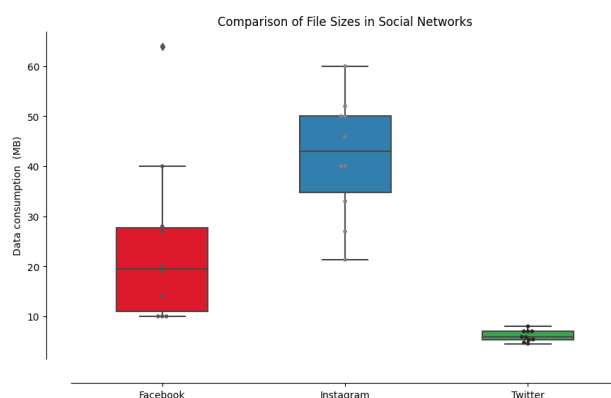


FIGURE 18 FILE SIZE FOR DIFFERENT SOCIAL NETWORK APPS

## 4.3. Effect of smartphones generation on energy consumption

The next figures 19, 20, and 21 show how much energy each of the three apps uses. It's obvious from all three cases that the type of smartphone you have makes a big difference. Pixel 5 consuming, on average, 20.83% more energy than Pixel 3.

Twitter App Energy Consumption under diffent Radio Acces Technologies

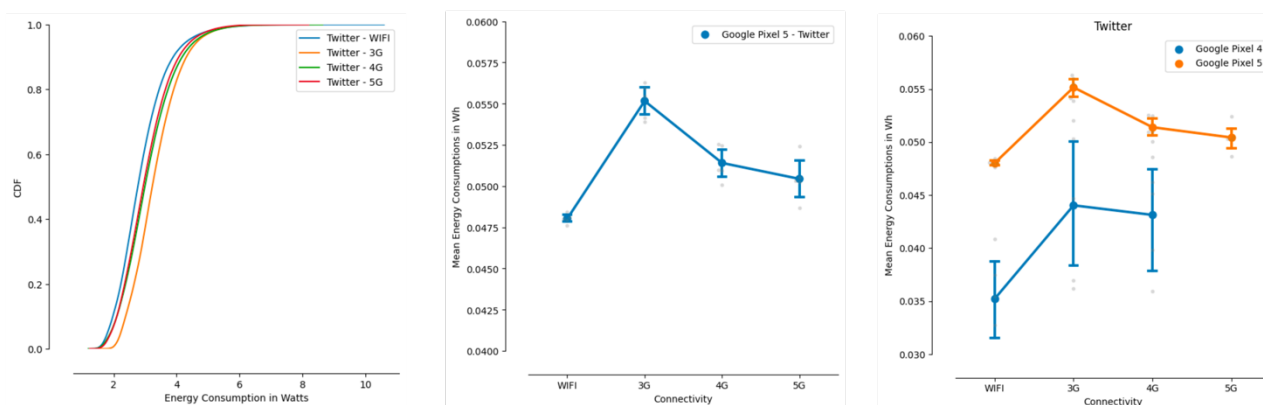


FIGURE 19 TWITTER ENERGY CONSUMPTION

Facebook App Energy Consumption under diffent Radio Acces Technologies

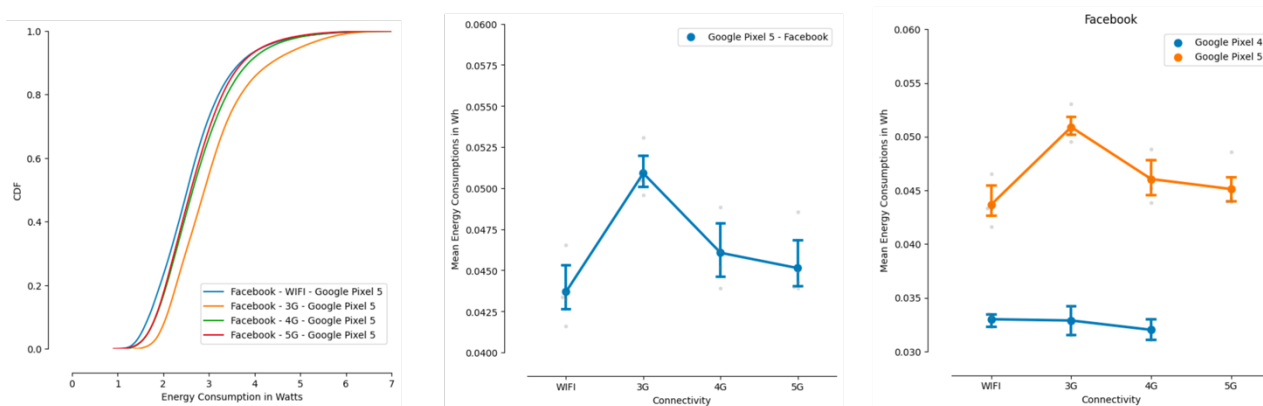


FIGURE 20 FACEBOOK ENERGY CONSUMPTION

Instagram App Energy Consumption under diffent Radio Acces Technologies

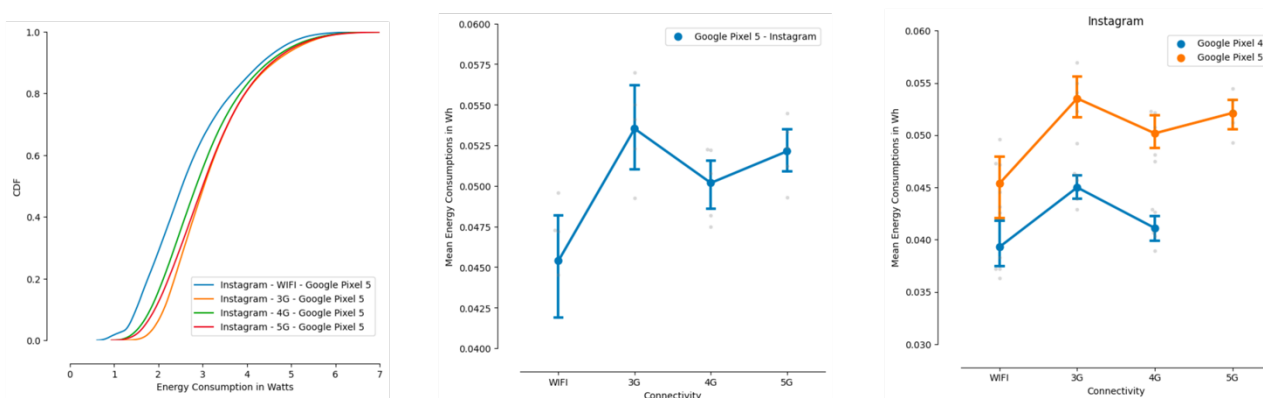
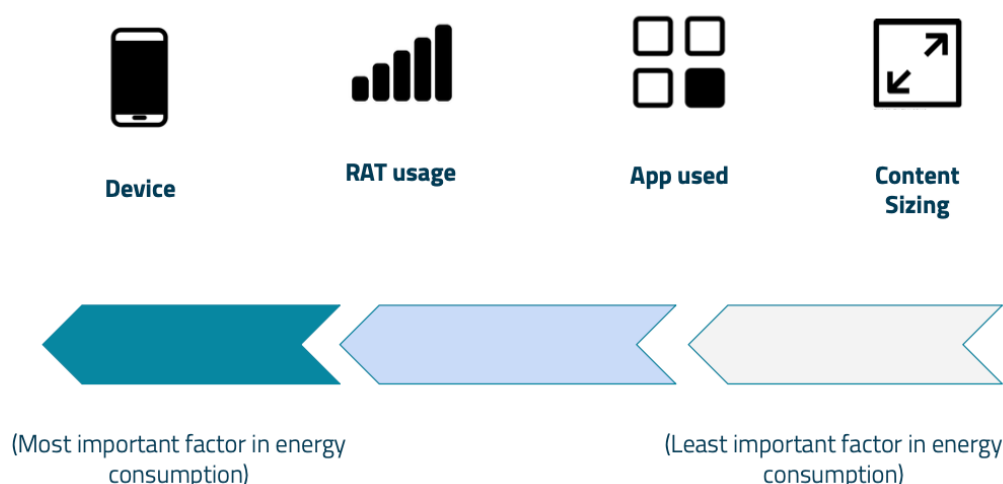


FIGURE 21 INSTAGRAM ENERGY CONSUMPTION

## 4.4. What drives energy consumption the most in the context of social network apps?

The Figure 22 below illustrates the primary and secondary factors influencing energy consumption. Specifically:

- i) Smartphone generation stands out as the most significant energy drain
- ii) Radio Access Technologies (3G/4G/5G/WiFi) exhibit a different energy consumption order compared to web browsing, with content download (and speed) appearing to influence it—WiFi emerges as the most efficient RAT, while 3G ranks as the least efficient
- iii) Unlike web browsing, content size is not correlated with energy consumption in this context
- iv) App selection carries more weight here than in web browsing, with Facebook being the most efficient app and Twitter being the least efficient



**FIGURE 22 FIGURE 16 IMPORTANCE OF DIFFERENT FACTORS IN THE CONTEXT OF SOCIAL NETWORK APPS**

## 5. Effect of RATs and machine learning application on energy consumption

We employed TensorFlow Lite to conduct an initial assessment of an image recognition task. While our findings are preliminary, they indicate that this type of application may be the most power-intensive among all tested. As depicted in Figure 27, power consumption remains consistently high throughout the experiment, likely due to the utilization of the smartphone's camera and the GPU-intensive image inference algorithm.

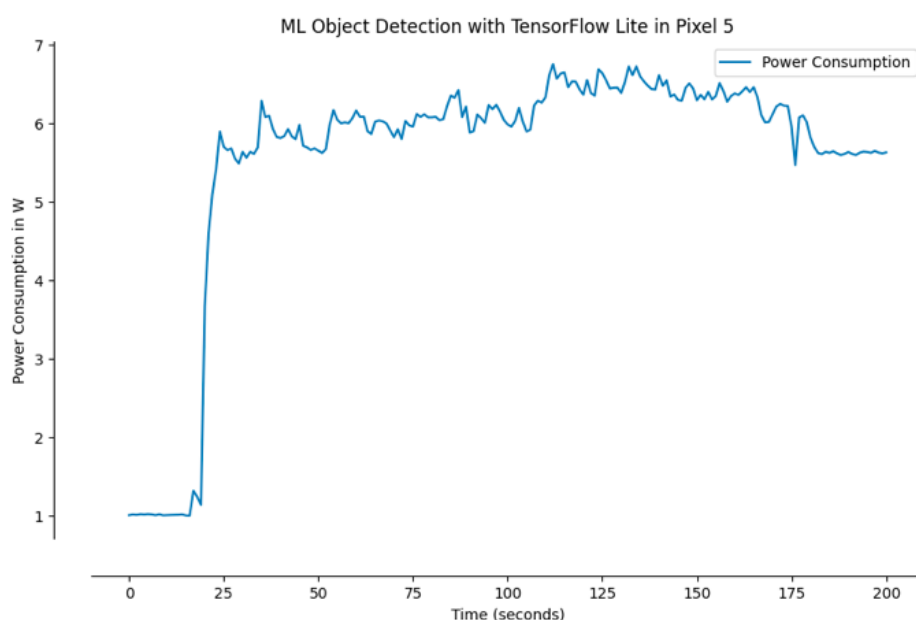


FIGURE 23 POWER CONSUMPTION WHEN PERFORMING OBJECT RECOGNITION

Additionally, Figure 28 illustrates a comparison between this machine learning-specific task and others. We observe that this type of application consumes approximately twice as much power as social networking, that also use in background AI/ML algorithms, however, they are running in the Cloud and not in the device.

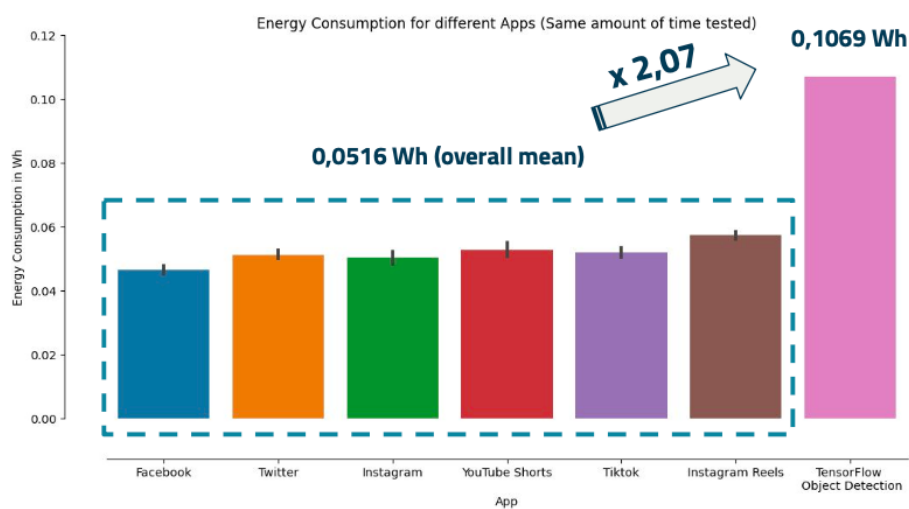


FIGURE 24 ENERGY CONSUMPTION FOR DIFFERENT APPS (TESTING TIME WAS FIX TO BE EQUAL AMONG ALL THE APPS)



## Summary and Conclusion

In summary, our investigation reveals that ML (Object Detection) applications exhibit heightened energy consumption compared to other domains. We've observed that energy consumption factors vary across different domains and network protocols. Across the board, newer generation devices consistently demonstrate higher power consumption.

The impact of Radio Access Technologies (RATs) on energy consumption is paramount, with varying efficiency depending on the domain. Generally, WiFi emerges as the most efficient RAT, while 5G tends to be less efficient.

By scrutinizing the inefficiency of 5G across the studied domains, we speculate on potential inefficiencies of 6G in future smartphone energy consumption. However, further studies and analyses are warranted to confirm these hypotheses.

In the browsing domain, content size proves pivotal in energy consumption, whereas in Social Networking and Streaming domains, content exhibits no clear correlation with energy usage.

Looking ahead, the final deliverable will present a detailed evaluation of the video streaming application, along with additional experiments on the other application types already analyzed in this report. Furthermore, we will extend our study to energy consumption at the base station level—a critical focus for telecom operators, as base stations account for approximately 70% of total energy usage in mobile networks. This final stage of the work will explore how different energy-saving policies influence both energy efficiency and overall system performance.

## References

- Narayanan, A. a.-L. (2021). A variegated look at 5G in the wild: performance, power, and QoE implications. *SIGCOMM*.
- Android. (2021). *Android 12*. Retrieved from Android 12: [https://www.android.com/intl/es\\_es/android-12/](https://www.android.com/intl/es_es/android-12/) - Last access: June 2024
- Android. (2023). *Android Debug Bridge (ADB)*. Retrieved from Android Developers: <https://developer.android.com/tools/adb> - Last access: June 2024
- Arlosoft. (2012). *MacroDroid Webpage*. Retrieved from MacroDroid: <https://www.macrodroid.com/> - Last access: June 2024
- GTmetrix. (n.d.). Retrieved from <https://gtmetrix.com> - Last access: June 2024
- Monsoon Solutions Inc. (2023). *HIGH VOLTAGE POWER MONITOR*. Retrieved from <https://www.msoon.com/high-voltage-power-monitor> - Last access: June 2024
- Raspberry Pi Ltd. (2019). *Raspberry Pi 4*. Retrieved from <https://www.raspberrypi.com/products/raspberry-pi-4-model-b/> - Last access: June 2024
- Statista. (n.d.). Retrieved from <https://www.statista.com/statistics/745319/mobile-phone-provider-market-share-in-spain/> - Last access: June 2024
- google. (n.d.). Retrieved from <https://www.google.com/> - Last access: June 2024
- magazine, t. (n.d.). Retrieved from <https://time.com> - Last access: June 2024
- movistar. (n.d.). Retrieved from <https://www.movistar.es> - Last access: June 2024
- times, n. y. (n.d.). Retrieved from <https://www.nytimes.com> - Last access: June 2024
- vodafone. (n.d.). Retrieved from <https://www.vodafone.es> - Last access: June 2024
- wikipedia. (n.d.). Retrieved from <https://www.wikipedia.org> - Last access: June 2024
- yoigo. (n.d.). Retrieved from <https://www.yoigo.com> - Last access: June 2024
- youtube. (n.d.). Retrieved from <https://www.youtube.com> - Last access: June 2024
- sandvine. (2021). *The Mobile Internet Phenomena Report*. Retrieved from [https://www.sandvine.com/hubfs/Sandvine\\_Redesign\\_2019/Downloads/2021/Phenomena/MIPR%20Q1%202021%2020210510.pdf](https://www.sandvine.com/hubfs/Sandvine_Redesign_2019/Downloads/2021/Phenomena/MIPR%20Q1%202021%2020210510.pdf) - Last access: June 2024