Data Analytics for Cybercrime and Undesirable Online Behaviors

Cross-Device Tracking

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Abstract

In this study, we address the complexities of cross-device tracking in the evolving digital ecosystem, focusing on the challenges posed by user behaviour and privacy considerations. We use python scripts to analyse large datasets from HTTP archives. Our methodology involves setting up a database to streamline analysis via SQL queries, targeting third-party domain requests, sensitive data transfer and cookie proliferation. We perform comparative analysis of cross-device behaviours and website categories to identify patterns in tracking activity. Our findings reveal intricate tracking mechanisms across devices and indicate varying levels of tracking intensity across different website categories. The study underscores the balance between effective tracking and privacy, and highlights the need for advanced solutions in CDT.

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1 Introduction

1.1 Overview

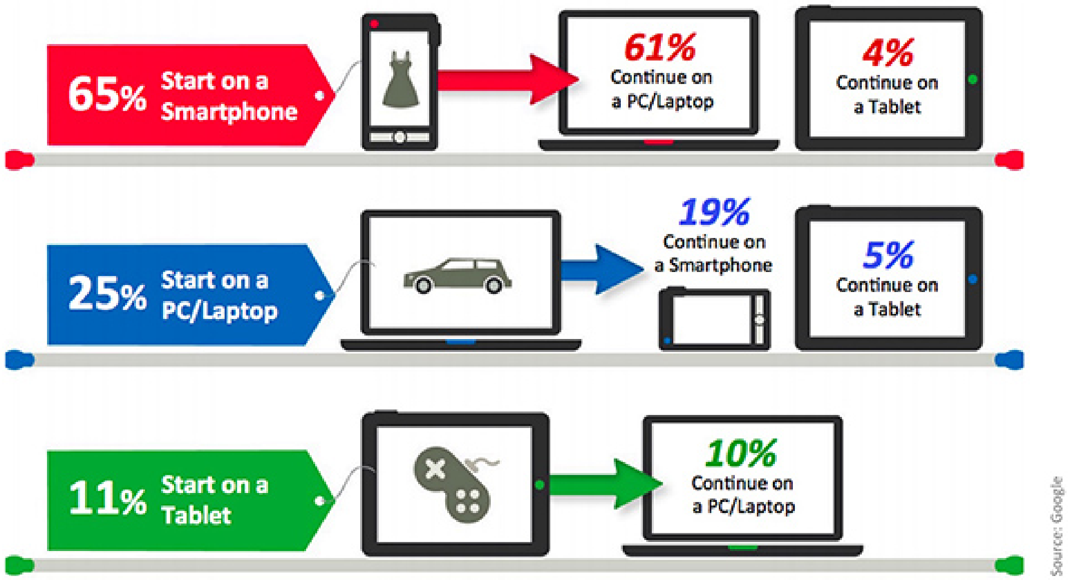
1.1.1 Definition

1.1.2 Purpose

1.2 Importance in Modern Digital Exosystem

1.2.1 Evolution of User Behavior

The digital landscape has seen a major evolution in user behavior, particularly in the way people interact with technology. In the early stages of the internet, user behavior was device-specific, primarily bounded to desktop computers. This era was characterized by more predictable online activities, with users typically accessing the internet from fixed locations and a small amount of different devices, which made user tracking relatively easy.



The invention of mobile technologies, especially smartphones changed online activities significantly and lead to a transformation in user behavior. Users began interacting with digital content across multiple platforms and often seamlessly switching between devices. For reference, Google published an interesting statistic, that shows more than 80 percent of all users switching their device during the user journey. Multi-platform interaction introduced a new level of complexity in understanding user behavior as users were no longer restricted to a single device.

Moreover, the rise of smart devices and the Internet of Things in the last years are the reason for even more complex interactions between devices. Today, a wide network of connected devices are creating a diverse and complex digital footprint.

1.2.2 Challenges in User Tracking

Parallel to the evolution of users online behavior, the task of tracking users across multiple devices has become increasingly challenging. As there exists no universal login system or consistent identifiers across different websites, establishing a meaningful user profile from disparate device usage is really complex.

Privacy considerations make cross-device tracking even more complicated. With increasing sensitivity to data privacy and the introduction of strong regulations like the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA), tracking users across devices must navigate the line between effective data collection and respect for user privacy and consent.

The diversity of devices and platforms results in fragmented data sources, requiring advanced technological solutions for data integration and analysis. The need for algorithms and technologies is necessary to not only gather but also accurately interpret the large amount of data generated by multi-device usage.

Looking ahead, these challenges will even intensify with the continuous evolution of technology. The integration of artificial intelligence and machine learning will potentially lead to advancements in user tracking, but also brings additional complexities regarding privacy regulations. The task of user tracking demands innovative solutions that are adaptable, take privacy into account and are able of decoding increasingly complex device interactions.

1.3 Techniques Employed in CDT

1.3.1 Deterministic Tracking

1.3.2 Probabilistic Tracking

1.3.3 Other Techniques

2 Study

2.1 Methodology

2.1.1 Data Collection

In the beginning our idea was to automate the data collection by using OpenWPM, a tool that automates the tasks of controlling a browser and collecting data. However, after some time it turned out that the general effort to set up such automation is not proportionate to the data we ultimately need. The only advantage would have been to replicate the user journey one-to-one and then possibly have more consistent data available. Nevertheless, we are now continuing with the manual data collection approach.

To analyze the cross-device tracking capabilities of various news websites, we conducted a systematic data collection using HTTP Archive (HAR) files. This process involved capturing network traffic data from both desktop and mobile devices. We selected our set of 20 websites by first categorizing them into news websites and shopping websites. These websites were chosen based on their popularity and the diversity of their content and geographical origin.

Prior to data collection, we created a test account on each of the selected websites. This was essential to ensure consistency in the user experience and to capture potential deterministic cross device tracking data across different sessions and devices.

To standardize the browsing environment and eliminate the most external variables, the data collection was executed using a virtual machine. This enables us to attribute any differences observed in the tracking mechanisms to the device type rather than other environmental factors.

Google Chrome was used as the web browser for this exercise as its developer tools with many functionalities allowed us to generate the HAR files.

The first part of the data collection involved accessing each news website from a desktop device. The user journey for all websites of both categories started with logging in using the previously created test account. For news websites the second part was navigating to a prominent news topic and try to imitate common user behavior. For shopping websites the second part included adding one or more items to the shopping cart and then proceed to checkout, but stop just before the actual payment.

The same procedure was replicated on mobile devices, to be more precise on an iPhone, in order capture the mobile user experience on the same websites. The HAR files of the mobile user journey was captured using Safari Developer Tools while connecting the iPhone to the MacBook via cable.

The resulting data set comprised 40 HAR files - 10 from desktop devices and 10 from mobile devices, corresponding to the same set of news websites and shopping websites. This data set will be the starting point for our subsequent analysis of cross-device tracking practices.

2.1.2 Data Analysis

cookieLog	
id	INT
domain	TEXT
host	TEXT
device_type	TEXT
website_type	TEXT

(a) cookieLog

emailHashes	
id	INT
host	TEXT
hash_type	TEXT
domain	TEXT
device_type	TEXT
website_type	TEXT

(b) emailHashes

thirdPartyLog	
id	INT
domain	TEXT
host	TEXT
device_type	TEXT
website_type	TEXT

(c) thirdPartyLog

Since our data is relatively large (50-100MB per HTTP archive), we performed most of the analysis using Jupyter Notebooks and the Python library haralyzer. In the initial stages of our data analysis, we began with a traditional approach, using print statements to inspect and debug the data. This method, while straightforward, quickly proved to be inadequate for handling larger datasets. As the volume and complexity of the data increased, it became apparent that a more robust and scalable solution was necessary. We then started to set up a database that includes three tables as displayed above, so we can perform the major part of our analysis with a small delay using simple SQL statements.

Our approach was then to determine which parts of the HTTP requests are relevant for us to make statements about cross-device tracking activities.

The first and perhaps most important part of our analysis consisted of filtering out HTTP requests that were sent to third-party domains. We are particularly interested in which domain the request was sent to and how often requests to such domains were recorded. We also wanted to compare the websites with each other in terms of the number of requests to third-party providers. We used the thirdPartyLog table in our database to filter and visualize the respective requests.

It is also interesting to see whether any sensitive data was sent to third-party providers. This means that we examine all HTTP requests and responses to see whether a simple, hashed or encrypted version of our email address can be found. We looked for plain and base64 encoded versions of our mail address as well as SHA1, SHA256, SHA224 and SHA512. In order filter and visualize our results, we used the emailHashes table of our database.

To get a general overview of the cookies set, we also wanted to determine the specific domains that have set the most cookies and possibly establish a correlation with the third-party domains that were requested the most. We focused on the quantity of cookies set by each domain, offering insight into the role these entities play in the broader context of online tracking, particularly in cross-device scenarios. We used the cookieLog table for this part.

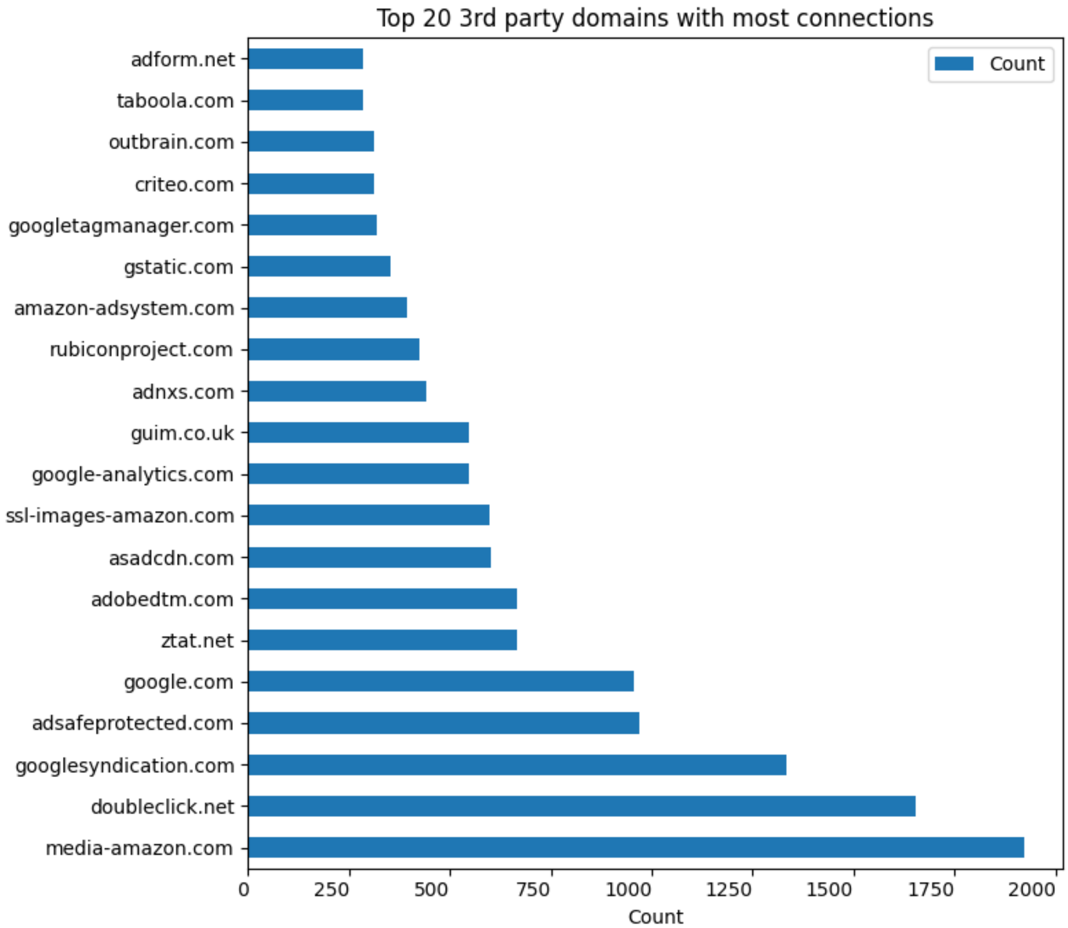
In order to also qualitatively analyze the cookies that were set, we looked at each website to see if there were identical cookies that were set for the same website on the desktop and the mobile device. To be even more specific, we checked which cookies could be identifiers that are used to uniquely identify a user across multiple devices so that, for example, customized advertising can be placed. This part is done manually as we have to look at possible identifiers by ourselves, because it is difficult to automatically filter out identifiers.

In the last part of our analysis, we wanted to carry out a comparative analysis. In fact, we have two variables that seem interesting for comparison. First, the device type, to show differences in behavior between mobile and desktop devices, and second, the website category by which we divided our websites in the initial step.

Our plan was to conduct the previous analysis again, but this time to differentiate and look at the relevant category. In the best case scenario, we can see interesting results that give an indication of which categories are more affected by cross device tracking activities.

2.2 Results

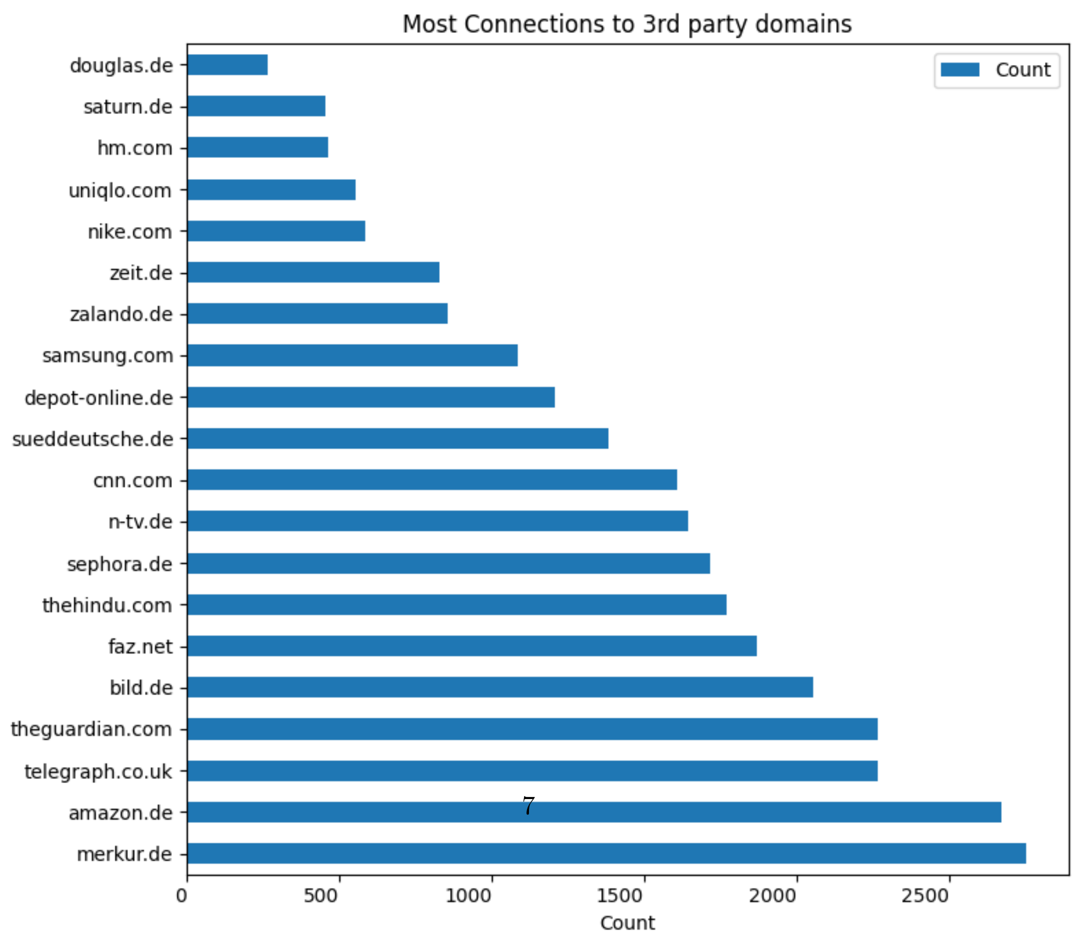
2.2.1 Requests to third party domains



Amazon
media-amazon.com
ssl-images-amazon.com
amazon-adsystem.com
amazon.com
cloudfront.net
amazonaws.com

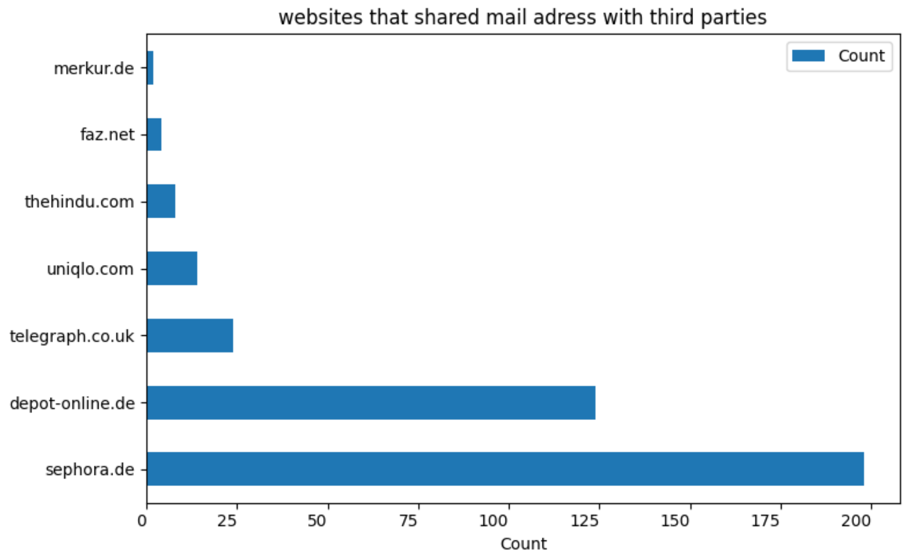
Google
doubleclick.net
googlesyndication.com
google.com
google-analytics.com
gstatic.com
googletagmanager.com
googletagservices.com
google.de
googleapis.com
googleadservices.com
recaptcha.net
youtube.com
ytimg.com

In our test runs on news and shopping sites we were able to identify links to a total of 537 different third-party domains. Overall, it was noticeable that most of the domains we found were connected to or part of Google and Amazon (see table). But we were also able to collect queries to other major tech companies such as Microsoft, Facebook and even TikTok. This shows once again how big a role these companies play in the context of online user tracking. Of course, this doesn't prove cross-device tracking, but it does give us an indication of how much data is being shared with third parties, and the likelihood that this data is being used to create accurate user profiles.

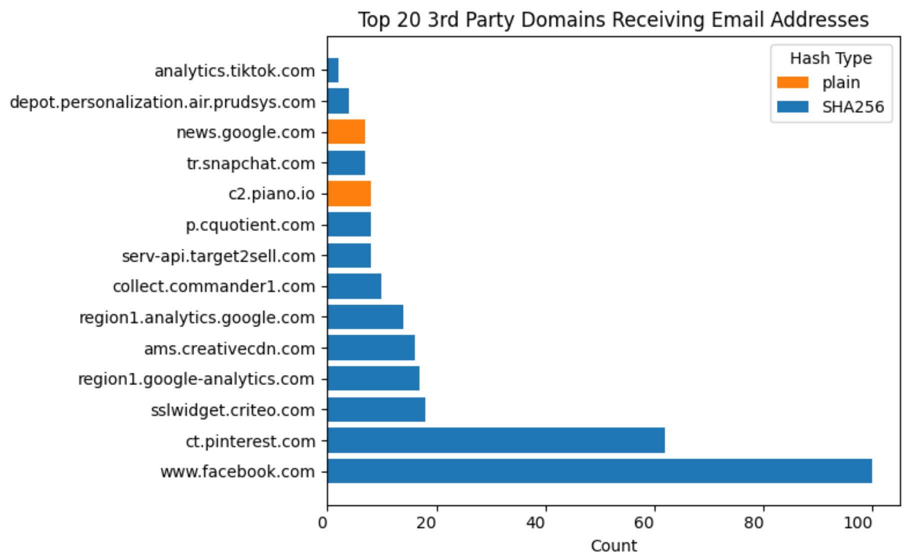


2.2.2 Sensitive Information to third party providers

In the study of sensitive information sharing with third parties, particularly focusing on email data, both hashed and plain, significant insights were revealed. The analysis centered on tracking the flow of email addresses to various third-party websites. The findings indicate a diverse range of websites receiving this sensitive data, with notable variations in the frequency and method of information sharing.



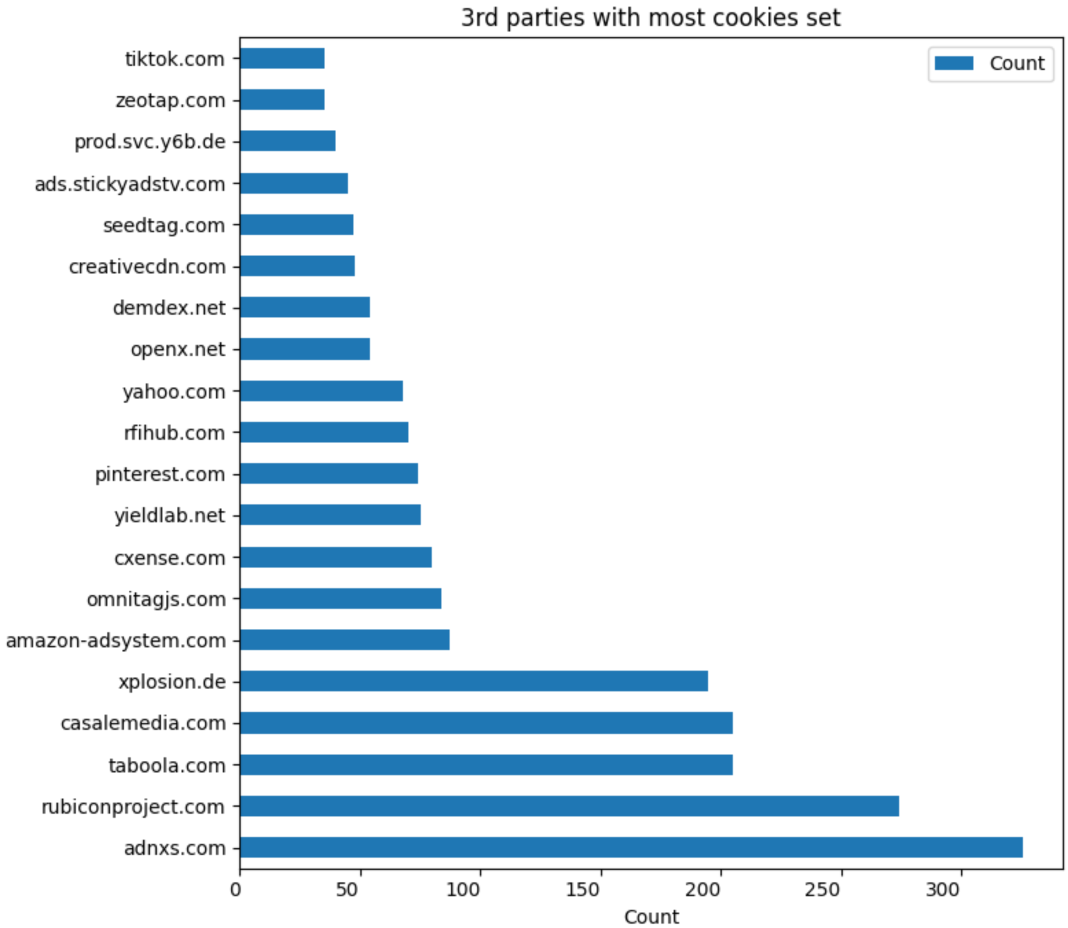
Moreover, when analyzing the encryption methods used, a predominant reliance on SHA256 hashing is observed. This pattern suggests a general preference for SHA256 as a security measure in the transfer of email data. However, instances of plain text email sharing are not absent, as evidenced by c2.piano.io and news.google.com, which shared email addresses 8 and 7 times, respectively, without encryption.



It should be noted that almost half of all email address transfers were initiated by Sephora. The sensitive data was in turn shared with big tech companies such as Facebook, Google and surprisingly even Snapchat and TikTok.

These findings raise critical discussions about the privacy and security measures in place for the transfer of sensitive data like email addresses. The varied use of encryption methods, along with the sheer number of third parties involved, highlights the complexity and potential vulnerabilities in the current digital landscape regarding data privacy.

2.2.3 Cookie Analysis



Certain domains, such as adnxs.com (AppNexus), taboola.com and rubiconproject.com showed a high frequency in cookies set and amount of connections from our test websites and were leading in terms of the number of requests, which indicates their comprehensive role in tracking and advertising across multiple platforms.

This underscores their significant role in the digital advertising ecosystem, especially in cross-device tracking. Amazon, through domains like amazon-adsystem.com and Google through domains like youtube.com, emerged as prominent trackers as well, but surprisingly despite having registered a high number of connections from our test websites, were much less dominant in cookie setting in comparison to the previously mentioned competing providers.

This finding suggests, that the big players are more likely to use alternative tracking mechanisms beyond traditional cookies, possibly including fingerprinting or pixel tracking.This finding aligns with its vast online presence and interest in user data for both e-commerce and advertising purposes.

The high volume of cookies set by these entities in genereal suggests an extensive network of data collection, crucial for building comprehensive user profiles across different devices.

2.2.4 Duplicate identifiers across mibile and desktop devices

As we have logged in in the beginning of all our test runs, it is likely that the websites have cross device tracked the test user via deterministic cross device tracking. Our analysis revealed several cookies with equal values across devices, indicating their potential use as cross-device identifiers. The relevant output can be found in appendix 1 and include:

1. DSID and User IDs: Various user ID cookies, were consistently found across devices. For instance, userId in faz.net and authId in sueddeutsche.de, with their unique alphanumeric strings, suggest a potential for user-specific identification across different browsing sessions and devices.
2. Encoded and Hashed Values: Cookies with base64 encoded strings (e.g., u in cnn.com) or hash values (e.g., hasheduseremail in sephora.de) were identified as consistent across devices. These formats are typically used to encode identifiable information in a non-readable format, enhancing security while still allowing for user tracking.
3. Unique Device or Session Identifiers: Cookies like UUID in merkur.de, with values that seem to be unique to each user, appeared consistently across different devices. This uniqueness is a strong indicator of their role in cross-device identification.

The presence of equal identifiers across devices underscores the sophisticated nature of current online tracking methodologies. These identifiers enable a seamless tracking experience, allowing advertisers and websites to create comprehensive user profiles by linking activities across multiple devices. This capability has significant implications for targeted advertising and personalized content delivery.

3 Comparison

3.1 Ecommerce websites vs news websites

3.2 Mobile vs desktop

4 Limitations and difficulties

5 Appendix

5.1 Duplicate Identifiers Output


```
Host: zeit.de
_pcus = eyJ1c2VyU2VnbWVudHMiOm51bGx9

Host: cnn.com
u = aHR0cHM6Ly9lZGl0aW9uLmNubi5jb20vYnVzaW5lc3M%3D
_cnn_uid = OTQxNTVhNTUtMGVjZC00ZGEzLWFmNzMtNTJjZjM1ZWQzN2M5

Host: faz.net
loginName = eWFubmlja25hc3RqYQ
```

```
userId = 3e53cfbaa80389a22720b68db84f527d
srvid = bb395a13b39656152115c1c3cdba904e

Host: merkur.de
_gali = id-subLvl1136460
UUID = eWFubmljay5uYXN0amFAZ21haWwuY29t
id_userid_pid = cd2499b88adfe913d527d757233bb865b447981e1bea34d74947547314c4279c

Host: sueddeutsche.de
_pprv = eyJjb25zZW50Ijp7IjAiOnsibW9kZSI6Im9wdC1vdXQifSwiMSI6eyJtb2RlIjoib3B0LW91dC...
_pcus = eyJ1c2VyU2VnbWVudHMiOm51bGx9
pa_user = %7B%22id%22%3A%22adb3877d-fcbc-4ec2-894f-6648ae74c4fe%22%7D
_pprv = eyJjb25zZW50Ijp7IjAiOnsibW9kZSI6Im9wdC1pbiJ9LCIxIjp7Im1vZGUiOiJvcHQtaW4ifS...
consentUUID = bbc5ad70-5a64-4521-8eb7-065208a1809a_26
authId = adb3877d-fcbc-4ec2-894f-6648ae74c4fe

Host: telegraph.co.uk
_pcus = eyJ1c2VyU2VnbWVudHMiOnsiQ09NUE9TRVIxWCI6eyJzZWdtZW50cyI6WyJMVHJldHVybjowZT...
_pcus = eyJ1c2VyU2VnbWVudHMiOnsiQ09NUE9TRVIxWCI6eyJzZWdtZW50cyI6WyJMVHJldHVybjowZT...
_pctx = %7Bu%7DN4IgrgzgpgThIC5QAUByBJAZgWwCbLwgFYA3MANhMVAAcYpMBLAD0RGYHsAvEAGhAAu...
consentUUID = e928ace6-ec18-4159-9597-1287a271b8d7_26
permutive-id = ae117a9a-37e0-4632-b69f-d912abc2843a
tmg_pid = PNIfmdPmds5vu6v

Host: thehindu.com
pubmatic-unifiedid_cst = zix7LPQsHA%3D%3D
AWSELB = D54D83371CA73269B30D9CD8F7A2329AB776287862C53884B438BAF2EA6E18262E3A59471...
AWSELBCORS = D54D83371CA73269B30D9CD8F7A2329AB776287862C53884B438BAF2EA6E18262E3A5...
_pctx = %7Bu%7DN4IgrgzgpgThIC4B2YA2qA05owMoBcBDfSREQpAeyRCwgEt8oBJAEzIEYOAmATgFYA7...

Host: zeit.de
_sp_v1_ss = 1:H4sIAAAAAAAAAItWqo5RKimOUbKKRmbkgRgGtbE6MUqpIGZeaU4OkF0CVlBdi1tCKRYA...
_pcus = eyJ1c2VyU2VnbWVudHMiOm51bGx9
_pctx = %7Bu%7DN4IgrgzgpgThIC5gF8A05owMoBcCGOkiIeAdgPakjoQCWOUAkgCbEDMAbAAwAsnAnDz...

Host: depot-online.de
__rtbh.uid = %7B%22eventType%22%3A%22uid%22%2C%22id%22%3A%2269638e8bc82beb01fbd95a...

Host: samsung.com
flpe = oaXGAjtvEtJfjmrX/h3xO/JAPowfwxiyWjDOZrRU11WabSV+iFR1bnPh3EHe+SG5+YsFSmlophN...

Host: sephora.de
hasheduseremail = 69638e8bc82beb01fbd95ae63968c186965aa5e18a4fd0b343639857d05be7c9
encrypteduserid = 4rS/rSHIyoF1mZh+BZr8PQ==
dwcustomer_5e55f69a7ebb6b69a6e78799321b1dea = acleQkaf6v8VEVIxhGRPj4qltU
__rtbh.uid = %7B%22eventType%22%3A%22uid%22%2C%22id%22%3A%224rS%2FrSHIyoF1mZh%2BBZ...
```

```
cquid = O0cMxg9O42I9Xo/AHRDIBN7BOlV6rfiTNnGAnGrpApU=|69638e8bc82beb01fbd95ae63968c...
cookie_user_id = 4rS%2FrSHIyoF1mZh%2BBZr8PQ%3D%3D
email = yannick.nastja@gmail.com

Host: uniqlo.com
bounceClientVisit6178v = N4IgNgDiBcIBYBcEQM4FIDMBBNAmAYnvgO6kB0ArgHYCWAjmAPZkDGjAt...
cquid = KFIMXY84g33OmCmbNc+6BivPb/wMpR6zwdUJWHKdE/4=|69638e8bc82beb01fbd95ae63968c...


theguardian.com, amazon.de, douglas.de, hm.com, zalando.de, n-tv.de, saturn.de,
nike.com
- no duplicate identifiers found
```

5.2 Github Repository

6 References