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Measuring Evolution of Cookie Dialogues

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Abstract

This thesis investigates how the cookie dialogues evolved in response to data protection regulations, introducing a scalable methodology that combines web archiving with machine learning to track these changes over time. We explore the usability of this method by applying it to the case study on French domains. Through this case study, we examined trends in cookie dialogue adoption linked to GDPR enforcement and CNIL fines and revealed noticeable shifts. Moreover, we have encountered limitations such as web scraping challenges and archival constraints, despite which the study provides valuable insights into the regulatory impact on privacy practices. This methodology offers a foundation for longitudinal analysis across various privacy compliance contexts.

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Chapter 1

Introduction

In recent years, cookie pop-ups have become a familiar part of the web browsing experience, informing users about data storage and sharing practices. However, these dialogues were not always mandatory, which led to inconsistencies and potential misuse. The ePrivacy Directive 2002 marked the first significant effort to protect user privacy. However, the introduction of the General Data Protection Regulation (GDPR) in 2016 set a new standard for data protection in the European Union. By 2018, enforcing GDPR with strict penalties for non-compliance started widespread changes across the digital landscape.

Despite these advances, there remains a critical challenge: assessing the real impact of these regulations on the evolution of cookie dialogues across different regions and languages. This study addresses this issue by developing a methodology to track and analyze the changes in cookie dialogues over time. The aim is to evaluate how data protection regulations have influenced the adoption and adaptation of these dialogues, providing insights into their effectiveness in enhancing user privacy. To explore this, the central research question is:

How can we evaluate the impact of data protection laws on the evolution of cookie dialogues?

Following the GDPR enactment, France's Data Protection Authority (CNIL) implemented additional regulations in 2019, further strengthening these protections. Our focus will be on tracing key legislative developments in France related to cookie dialogue compliance and examining how they have influenced the evolution of cookie dialogues on French websites.

To answer the main question, we are going to investigate the following sub-question:

How can we leverage a web archive to create a timeline of cookie dialogue changes over a period of time for a specific case?

Throughout our case study, we aim to use the WayBack Machine together with the machine learning model to track and analyze changes in cookie dialogues across French websites. Our goal is to develop a methodology that can be applied to multiple languages within the European Union domain, helping to contribute to researching this area of web privacy.

Contributions. In response to the challenges of assessing the evolution of online privacy practices, this thesis proposes an approach to tracking the appearance and adaptation of cookie dialogues over time. By combining the archival capabilities of the WayBack Machine with the XLM-RoBERTa model for multilingual classification, the thesis provides insights into how GDPR and CNIL regulations shaped compliance behavior in the digital space.

The main contribution is creating a method that tracks cookie dialogue adoption and its potential applications for policymakers, researchers, and privacy advocates. This data can be used to assess the effectiveness of privacy regulations, track compliance patterns, and even identify periods of increased regulatory enforcement, such as when significant fines were imposed. Additionally, this research introduces a scalable, automated approach to studying legislative impacts, which makes it adaptable to future studies across different countries, languages, and timeframes.

Moreover, the methodology's flexibility allows it to be adjusted to examine other web-based tasks beyond cookie dialogues, contributing to broader research areas like privacy, security, and web analytics. The findings would also help develop more advanced tools to refine cookie dialogue classification and improve accuracy in detecting regulatory shifts.

Ethical Considerations. This thesis places ethical considerations at the forefront of studying how web services adapt to privacy regulations guidelines. By Adhering to the Menlo Report's ethical framework [1], we ensure responsible research conduct.

We abstain from gathering personally identifiable or sensitive data during crawling and filter out illegal or unethical websites from the analysis. Our use of the WayBack machine aligns with digital heritage preservation in accordance with its terms of service.

We sustain intellectual property rights and copyright regulations and implement responsible crawling practices to minimize disruption. These measures guarantee ethical research conduct, promoting trust and the responsible utilization of web crawling and the WayBack Machine.

[1] The Menlo Report: Ethical Principles Guiding Information and Communication Technology Research.

Chapter 2

Background

This chapter provides the context needed to understand the evolution of cookie dialogues in response to Data Protection Regulations (DPRs). It covers key topics such as the regulatory framework, the technical tools used for data collection and analysis, and the relevant concepts of cookies and consent mechanisms. A detailed timeline of privacy regulation changes can be seen in Appendix A.

2.1 Data Protection Regulations (DPRs)

Data Protection Regulations (DPRs) are legal frameworks designed to protect individuals' data and ensure privacy. These frameworks establish guidelines for collecting, processing, and storing personal data.

ePrivacy Directive (ePD). The ePrivacy Directive (ePD), also known as the "Cookie Directive," was enacted by the European Union in 2002 and later amended in 2009 [1]. It complements the GDPR by specifically addressing privacy and electronic communications. The ePD requires websites to obtain informed consent from users before storing or accessing information on their devices, most notably through cookies. This directive laid the groundwork for cookie consent mechanisms, emphasizing the need for transparency and user control over personal data long before the GDPR expanded these requirements across all forms of data processing.

General Data Protection Regulation (GDPR). The General Data Protection Regulation (GDPR), enacted in May 2018 [2], is a comprehensive regulation by the European Union aimed at enhancing data protection and privacy for all individuals within the EU. It introduces stronger consent requirements, mandates data breach notifications, and grants individuals the right to access and delete their personal data. The GDPR has significantly influenced how organizations handle this data, including implementing consent mechanisms.

[1] ePD 2009.
[2] GDPR 679/16.

Commission Nationale de l'Informatique et des Libertés (CNIL). CNIL is the French Data Protection Authority responsible for enforcing GDPR and other data protection laws in France. CNIL has issued specific guidelines[3] on cookie usage and consent, which have shaped how French websites implement cookie dialogues.

2.2 Cookie Banners and Dialogues

Cookie banners and dialogues are mechanisms implemented by websites to obtain user consent for cookie usage. Since the introduction of the GDPR, these tools have significantly evolved in both design and functionality to ensure compliance while maintaining user attention.

The GDPR introduced specific regulations concerning cookie consent mechanisms, emphasizing explicit user consent, the types of cookies used, and their purposes. On the other hand, cookie banners are usually displayed as pop-ups when a user first visits a website, serving as the initial point of interaction. These banners inform users about the website's cookie usage to ensure we understand its operations and may provide options for managing cookie preferences.

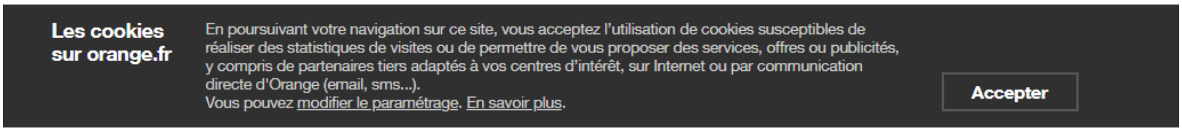


Figure 2.1: Example of a cookie banner before GDPR taken from https://www.orange.fr/ April 2018.

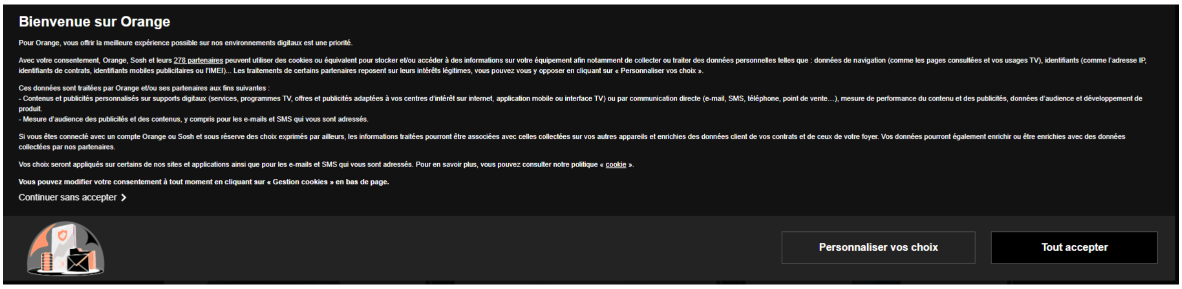


Figure 2.2: Example of a cookie dialogue after GDPR taken from https://www.orange.fr/.

Cookie dialogues go beyond basic notifications by offering users detailed information about the types of cookies used and the ability to accept or reject them. This approach informs users about more significant control over their data, aligning with the regulatory requirements of the GDPR [4]. The transition from simple cookie banners to more explicit cookie dialogues represents an evolution started by the GDPR's focus on data transparency as well as user control. Examples of such change can be seen in Figures 2.1 and 2.2.

For a detailed overview of GDPR requirements related to cookies, please refer to Appendix A.

[3] CNIL regulation.
[4] GDPR 679/16.

2.3 Tranco List

The Tranco list is a widely recognized and extensively used web measurement and analysis tool. Similar to services like Alexa [5] and Majestic [6], Tranco provides a ranking of the top websites based on their popularity and visibility on the internet [LPVGT^{+}19]. The list is populated by collecting data from different sources, including web crawls and search engines, and ranks the top websites in descending order based on their traffic. While the ranking criteria may vary, they generally consider factors such as the number of unique visitors, incoming links, and domain authority. A Tranco list consists of a fixed number of websites referred to as the *Tranco Top N* websites. The N value can vary for a specific version of the list, e.g., a Tranco list of the top 10,000 most popular websites. Users can extract a copy of a list from a specific date, making it a practical and informative tool for historical analysis of changes in internet traffic over a specific period. Additionally, Tranco List can be customized to fit specific needs, such as filtering by country or region, adjusting list size, or including specific categories or domains, helping targeted examination within specified parameters.

2.4 WayBack Machine

The WayBack Machine is a crucial tool for digital preservation, providing an extensive archive of the World Wide Web [7]. Its vast database is invaluable for researchers, historians, and anyone interested in studying the evolution of web content.

The WayBack Machine uses automated crawlers to visit and download web pages to store them in its database. Users can access this archived information by entering a URL into the search bar, which then displays a calendar view with the dates when the page was archived or using dedicated APIs.

- **Digital Archive**: Allows users to view historical versions of web pages, offering a snapshot of the internet at different moments.
- **Extensive Database**: It has archived over 735 billion web pages [8], making it one of the largest digital archives globally.

2.5 Selenium

Selenium is an open-source framework designed to automate web browsing tasks [GGGMO20]. It is helpful for developers and testers to simulate user interactions, execute automated tests, and extract necessary data from web pages. Selenium performs interactions between code and web browsers, which allows for the automation of repetitive tasks and the reduction of manual effort.

[5] https://www.alexa.com
[6] https://majestic.com/reports/majestic-million
[7] http://web.archive.org
[8] The WayBack Machine general info.

2.6 Web Crawling and Web Scraping

Web Crawling. Web crawling involves systematically browsing the internet to observe web content, which helps identify and access relevant websites.

Web Scraping. Following identifying relevant websites through web crawling, web scraping extracts specific data from these pages. This technique collects precise information such as text, images, and links, useful for detailed web content analysis.

2.7 Bootstrapping

Bootstrap sampling is a statistical technique used to estimate the properties of an estimator, such as its variance, by sampling with a replacement from an observed dataset [ET93]. This method is particularly effective when dealing with small datasets or when the underlying distribution of the data is unknown. The process involves four key steps:

1. **Original Sample Selection**: Start with a single sample dataset, which forms the basis for creating the bootstrap samples. This dataset might consist of the observed data from an experiment, such as information on cookie dialogues.
2. **Resampling**: Generate multiple new samples, known as bootstrap samples, by randomly selecting data points from the original sample with replacement. That means the same data point can appear multiple times in a single bootstrap sample. Each bootstrap sample is the same size as the original dataset.
3. **Statistical Calculation**: For each bootstrap sample, calculate the desired statistic, such as the mean, median, or variance. This step results in a distribution of estimates, one for each bootstrap sample.
4. **Aggregation**: Analyze the distribution of the bootstrap statistics to get a better idea about the population. That can involve calculating the mean and confidence intervals for the statistic across all bootstrap samples, providing a robust estimate of the variability in the data.

In research, bootstrap sampling can evaluate the stability and reliability of observed data and guarantee that the results are consistent and representative, even with limited or varied data.

Chapter 3

Related Work

In the first part of this section, we will dive deeper into available research that aims to track cookie practice changes in response to data protection regulations. In the second part, we will talk about studies that used the WayBack Machine service for longitudinal researches.

3.1 Measuring the Impacts

The landscape of online privacy is intricate and continually evolving, with data regulations such as the GDPR aiming to enhance user control over personal information. However, we understand that assessing the real-world impact of these regulations on privacy practices presents significant challenges. This section reviews studies that use various methodologies and approaches for measuring and analyzing the effectiveness of privacy regulations, mainly focusing on consent notices and cookie consent mechanisms.

A study by Utz et al. examines the user interface of consent notices, a relatively unexplored area in GDPR compliance research [UDF+19]. Researchers aimed to understand common properties of consent notices by analyzing a dataset compiled from over 6,000 unique domains. This process involved using a Selenium-based automated browser setup to capture screenshots and manually check for the presence of consent notices. While the detailed manual verification provides insights, it also underlines the need for automated methods that align with our research objectives.

Exploring another dimension of GDPR compliance, Soe et al. investigate the use of dark patterns in cookie consent mechanisms across 300 online news outlets [SNGS20]. Through a manual review of Scandinavian and English-language news websites, the researchers identified unethical practices designed to manipulate user consent. This work highlights the importance of examining design choices in consent mechanisms, which aligns with our goal of automating the detection and classification of such patterns on a larger scale.

To analyze the GDPR impacts on browser cookies, Dabrowski *et al.* has conducted a longitudinal study on collected cookies from Alexa's Top 100,000 websites where they compared the cookie behavior from 2016 to that nowadays to see the behavior change. The study reveals that around 49.3% of Alexa Top 1,000 websites only set cookies after the consent is granted when facing an EU visitor. This number drops by half when observing the Alexa Top 100,000 websites. These findings raise an important issue regarding the trend of less popular websites in slower adaptation to privacy regulations.

Furthermore, research by Zhuo et al. investigates the impact of GDPR on internet interconnection by analyzing traffic patterns before and after the regulation's implementation [ZHCG21]. By examining internet traffic data, the study looks for shifts in data flows and changes in privacy practices across networks, identifying alterations in data routing and processing practices caused by GDPR. A fundamental limitation was the difficulty attributing all observed changes directly to GDPR due to simultaneous global shifts in data practices. This study is particularly relevant to our method because it attempts to identify changes in traffic caused by data protection enforcement, reflecting our goal of detecting shifts in cookie practices.

3.2 Leveraging the WayBack

The WayBack Machine, as an extensive web archive, has been used in various studies to investigate the impact of privacy regulations over time. While its application in privacy research is still developing, several studies have demonstrated its utility and highlighted its limitations.

To illustrate the efficacy of the WayBack Machine in recovering web content, Kumar *et al.* examined the rate of loss for online citations. They analyzed URL citations from journals and conferences to determine their persistence on the web. Using the WayBack Machine, they recovered content from vanished citations, showcasing its effectiveness. However, they also noted that only half of the web pages were archived, noting a need to improve the service's coverage [KKP15, KP15].

Building upon this foundation, Hashmi *et al.* used the WayBack Machine to study the evolution of ads and tracking domains over time. By collecting data from selected websites between 2009 and 2017, they analyzed changes in blacklists. The study pointed out limitations of the WayBack Machine in terms of redirections and inconsistent archiving frequencies, which could result in missed data [HIK19], highlighting a critical aspect we need to consider in our longitudinal analysis of cookie dialogues.

Further extending the application of the WayBack Machine, a study of Hadi *et al.* examined the evolutionary behavior of bug reports. Researchers explored the history of bugs, comparing resolved and open bugs over a decade. They used a machine learning algorithm to validate their findings, showing the WayBack Machine's application in tracking web elements over time [JCNS+22].

Similarly, Degeling *et al.* focused on changes in privacy policies post-GDPR implementation, using the WayBack Machine and a crawler for a semi-automated analysis across different countries. They found increased transparency could lead to a false sense of security and suggested a multi-lingual approach [DUL+19]. This recommendation is pertinent to our research, as our model is designed for multi-lingual data analysis.

Finally, Dausend *et al.* evaluated GDPR compliance by manually checking 466 websites for cookie notices using the WayBack Machine. They observed minimal impact on cookie compliance practices in Germany and the US, highlighting the varied responses to GDPR [Dau23]. This study emphasizes the need for comprehensive, automated methodologies to understand compliance trends across regions better.

In conclusion, these studies highlight the WayBack Machine's potential and longitudinal web data analysis limitations. We find it useful to consider for our approach in developing a robust methodology for analyzing cookie dialogues over time.

Chapter 4

Methodology

In this chapter, we present a flexible methodology designed to study the evolution of cookie practices. Researchers can define their specific goals for the investigation, apply this methodology to a selected list of websites, and extract the first screen of cookie dialogues and their content from these sites over a chosen period. This process allows a direct and focused analysis of changes in cookie practices designed to address specific research questions. It also ensures that the methodology can accommodate a variety of research objectives and adapt to different investigative contexts.

The methodology for our study is structured into three distinct phases, each designed to support the overarching goal of capturing and analyzing the evolutionary changes in cookie dialogues. Each phase focuses on tasks contributing to the comprehensive collection, classification, and data analysis.

1. **Historical Web Data**: The first phase involves obtaining a list of pages from the WayBack Machine archive to get a diverse and representative dataset. The aim is to gather numerous web pages efficiently for in-depth analysis.
2. **Collecting Web Elements**: Once the web pages are identified, the next step is to collect web elements from the list of pages systematically. We use web scraping to extract large amounts of detailed information about cookie dialogues and consent buttons.
3. **Classifying cookie dialogues and buttons**: In this phase, the collected cookie dialogues and their associated buttons are subjected to detailed classification. We use multi-lingual data classification with the XLM-RoBERTa model to analyze the cookie dialogues' textual and structural elements.

Each phase is designed to build upon the previous one, creating a layered approach to data collection and analysis that enhances the reliability and depth of our findings. Figure 4.1 illustrates the general idea of our method. We give an example of possible research tasks to highlight the idea that our method can be used to investigate different aspects of cookie dialogues.

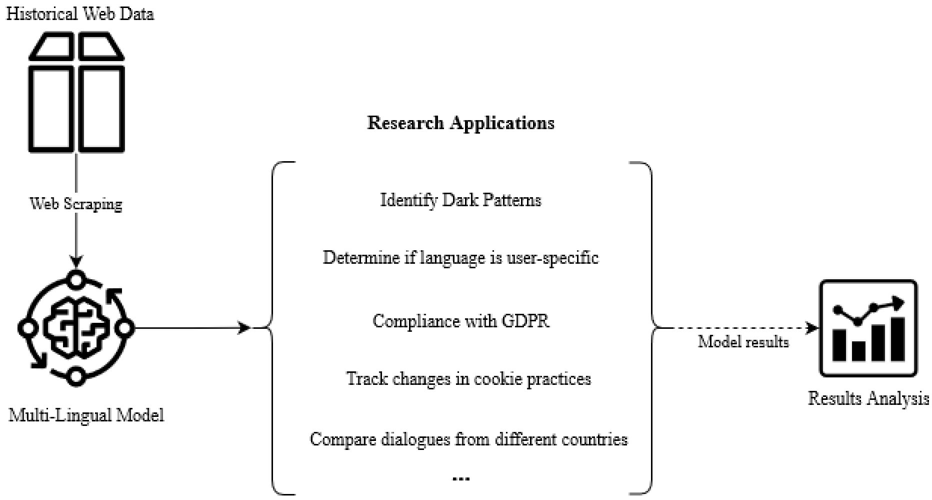


Figure 4.1: Method overview

4.1 Historical Web Data

Website Selection. In this research, we focus on analyzing the most popular websites with EU top-level domains (TLDs). While several services offer metrics on website popularity, these rankings often vary by using different measurement criteria and being susceptible to manipulations.

Services like Majestic SEO's Majestic Million and Alexa's Top Sites use distinct approaches to rank websites. Majestic Million, for example, ranks websites based on the number of subnets hosting a page. It is updated daily, primarily focusing on backlink analysis. On the other hand, Alexa emphasizes traffic volume and audience demographics to determine its rankings. However, research by Le Pochat et al. [LPVGT+19] highlights the potential for manipulation in these popular rankings, demonstrating how much services like Alexa, Cisco, Majestic, and Umbrella can be influenced. In response, these researchers introduced Tranco, a new ranking service that uses lists from Alexa, Cisco, Majestic, and Umbrella to create a more robust and less manipulable index.
Tranco enhances website rankings' validity, consistency, and verifiability by filtering out unavailable and malicious domains. This approach results in a minimal daily change of at most 0.6%, providing a stable and reliable foundation for data collection. Given its resilience against manipulation and its comprehensive aggregation methodology, Tranco's ranking is chosen for our study to ensure the robustness and reliability of the data we collect.

Web Archive Selection. Selecting an appropriate tool for retrieving historical web data is essential for effectively studying the evolution of web content. The tool must offer detailed chronological records, contain many websites, and ensure accurate content capture.

Archive.today [1] allows for manual, on-demand archiving of specific pages. Although useful for

[1] https://archive.ph.

focused data collection, it does not provide the systematic, periodic data collection necessary for broad temporal analyses. In contrast, search engine caches from providers like Google [2] and Bing [3] offer rapid access to recent web page snapshots. However, these caches do not maintain a long-term historical archive, making them unsuitable for longitudinal studies.
Common Crawl [4] captures a wide selection of internet data monthly, which is useful for identifying broad trends. However, the monthly interval is too broad to capture the nuances studies require to track the impacts of specific events or regulatory changes more frequently. The WayBack Machine captures websites more frequently and provides broader historical coverage.
Therefore, we believe the WayBack Machine is the most suitable choice. It fits the requirements for detailed, accurate, and extensive analysis of historical web data. While no tool can guarantee complete data capture, the WayBack Machine's archiving functionality significantly reduces the likelihood of missing critical data, making it valuable for our research that demands high reliability and comprehensive scope.

4.2 Multi-lingual Data Classification

To classify cookie dialogues from web pages in multiple languages, we consider different machine learning models known for their robust handling of language nuances.

Before evaluating specific models, it is essential to understand the foundational technology upon which many are built. In the study by Van Hofslot *et al.*, a classification model BERT (Bidirectional Encoder Representations from Transformers) and its variations have been used to evaluate cookie banner legal regulation violations, focusing on the language used [VHASGS22]. The study showed that BERT and its variation LEGAL-BERT had the highest accuracy (70%-97%). BERT is a breakthrough in machine learning, particularly in natural language processing (NLP) [DCLT19]. Training language models based on the entire set of words in a sentence or query (bidirectional) allows the model to grasp context more effectively, significantly improving its ability to understand and generate human-like responses. We evaluated several models for their potential to provide accurate and efficient multi-lingual classification:

mBERT (Multilingual BERT): An extension of the original BERT model, mBERT is trained on Wikipedia data in 104 languages, making it capable of processing text in multiple languages. However, its reliance on Wikipedia as a training dataset may limit its applicability to diverse web vernaculars [PSG19].

DistilBERT: This model offers a streamlined version of BERT that maintains much of the original model's performance but at a reduced complexity and resource requirement. While efficient, its simplified nature may lack depth in capturing complex nuances in cookie dialogue analysis [SDCW20].

T5 (Text-to-Text Transfer Transformer): Unlike BERT, which directly handles classification and question-answering tasks, T5 converts language tasks into a unified text-to-text

[2] https://www.google.com.
[3] https://www.bing.com.
[4] https://commoncrawl.org.

format, such as translating text or summarizing information, which could risk losing nuances in complex legal or technical terminology when applied to a multi-lingual dataset [RSR+23].

XLM-RoBERTa: After evaluating these models, we find that XLM-RoBERTa is superior for our multi-lingual classification task. This model is a refined iteration of the original BERT architecture, significantly enhanced to facilitate multilingual processing. Unlike BERT and its direct successor, RoBERTa, XLM-RoBERTa leverages the extensive Common Crawl web data, which contains content in over 100 languages [LOG+19]. This varied dataset significantly reinforces XLM-RoBERTa's capacity to grasp and interpret language variations across diverse linguistic backgrounds.

Empirical studies, such as those conducted by Conneau et al., have shown that XLM-RoBERTa surpasses various BERT variations, including mBERT, in multiple Natural Language Processing (NLP) tasks. It performs well in text classification and sentiment analysis across different languages, demonstrating superior performance [CKG+20].

RoBERTa-LSTM Hybrid: In exploring effective models for multi-lingual classification, the hybrid model that combines RoBERTa with Long Short-Term Memory (LSTM) networks is worth discussing. This hybrid model aims to merge RoBERTa's deep contextual understanding with the sequential data processing capabilities of an LSTM, potentially enhancing the model's ability to process and analyze longer and more complex text [TLAL22]. While theoretically promising, this combination introduces additional complexity to the model architecture. Integrating LSTM with RoBERTa's already robust framework might not give equivalent benefits, especially compared to less complex models. Therefore, we choose to use **XLM-RoBERTa** due to its effectiveness in multi-lingual environments that align with our research objectives.

4.3 Proof of Concept Implementation

To conclude the Methodology section, we present an overview of our Proof of Concept (PoC) implementation, which can be seen in Figure 4.2. This diagram illustrates the practical application of the proposed method, showing the flow from data acquisition to analysis.

As depicted in Figure 4.2, the process begins with retrieving a list of popular websites using the Tranco list. These websites are then accessed through the WayBack Machine Archive via API calls to fetch historical web pages. The collected web pages undergo web scraping to extract cookie dialogues and consent buttons. These elements are then analyzed using the XLM-RoBERTa classification model to categorize cookie dialogues and buttons accurately. The classified data is gathered into a list, which is later analyzed to determine trends and patterns in cookie dialogue practices.

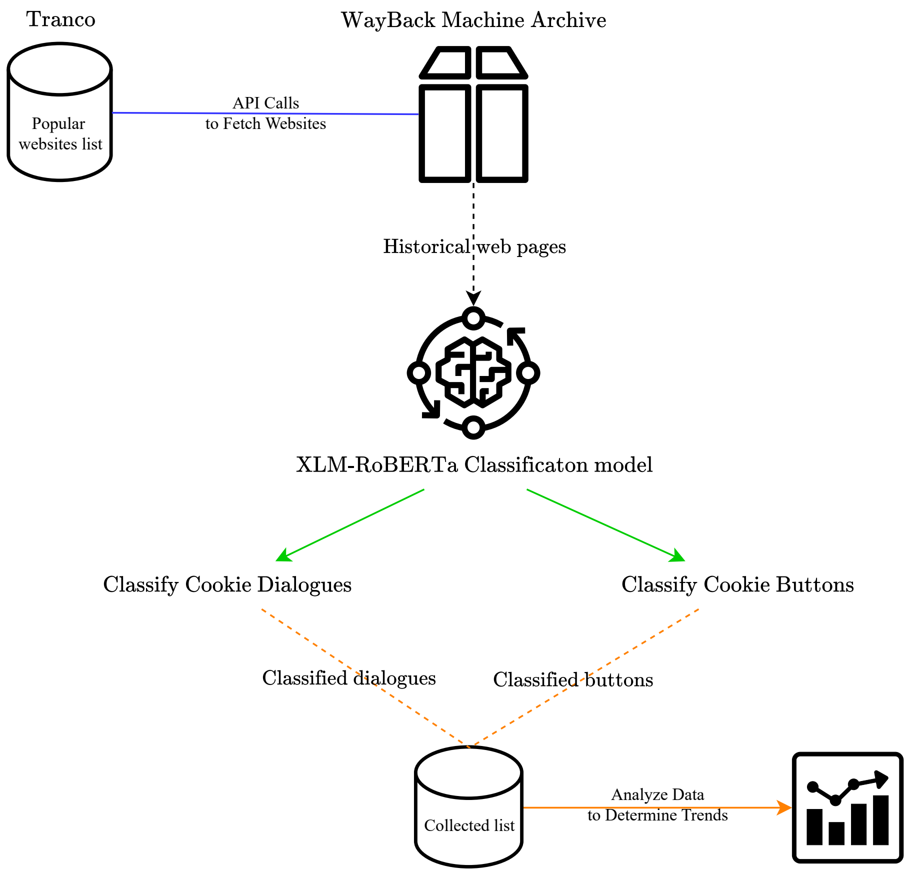


Figure 4.2: Proof of Concept Implementation Diagram

Automated Data Collection with Selenium and Firefox. We use Selenium together with the Firefox browser for the automated collection of web elements. Selenium automates the browsing process, allowing us to systematically visit websites and interact with their cookie dialogues, which is not just a convenience but a necessity for handling large datasets. It ensures that our study can scale effectively without manual intervention, promoting the scalability of our method.

Cookie Dialogues and Banners. In our study, cookie dialogues and banners are treated as equivalent due to the ambiguity in regulatory guidelines from the GDPR and enforcement action from data protection authorities such as CNIL. That is because we are working with older versions of legislation; therefore, these terms are often interchangeable.

Chapter 5

Case study: evolution of French cookie dialogues

This chapter provides a specific case for the proposed method to analyze its usability and discuss the results. We explain why this specific case study was chosen to evaluate the method. Then, we will describe the experiment and provide a glimpse of the implementation. We will present the results of the case study as well as their analysis and validation. Finally, we will have a discussion on the outcomes of this study and what it means for our method.

5.1 Case Study Set Up

We will apply our proposed methodology to a specific case study framework to evaluate its effectiveness and feasibility. Our objective is to select a European country subject to the General Data Protection Regulation (GDPR) [1] with a strong Data Protection Authority (DPA) and notable history of enforcing data protection laws. Additionally, we aim to demonstrate the effectiveness of our chosen machine learning model, XLM RoBERTa, by selecting a domain where the primary language is not English. Given these criteria, France, with its national DPA, the Commission Nationale de l'Informatique et des Libertés (CNIL) [2], emerges as an ideal candidate. This case study will analyze the emergence and evolution of cookie dialogues and consent buttons over a period that correlates with GDPR and CNIL enforcement actions.

Focus on Popular Websites. We first retrieved the Tranco Top 1 million most popular websites using the Tranco list [3] service generated on February 20, 2019. Although our original plan was to use data immediately following the GDPR compliance deadline, constraints led us to use the earliest available Tranco list. Despite the slight delay, this dataset remains representative of the Tranco Top 1 million popular websites at that time.

We focus on these popular websites because they are under intense scrutiny from Data

[1] GDPR 679/16.
[2] CNIL regulation.
[3] https://tranco-list.eu

Protection Authorities (DPAs) due to their significant traffic volumes and the large amounts of user data they process. These sites are more likely to be targeted by regulatory authorities for compliance checks, which makes them prime candidates for studying the evolution of cookie practices. Their high visibility also means that any changes in their cookie policies will likely influence broader industry trends, thus providing valuable insights into the effectiveness of GDPR and CNIL regulations.

Date Range. To create a timeline of the appearance of cookie dialogues, focusing on the periods influenced by GDPR and CNIL regulations, we have selected a date range from April 2016 to April 2021. That aligns with key legislative events, providing a comprehensive five-year period for analysis (see Appendix A for detailed dates).

- **GDPR Regulation (EU) 2016/679:** Date of issue: 27 April 2016; Adaptation date: 25 May 2018 [4].
- **CNIL:** Date of issue: 17 September 2020; Adaptation date: 31 March 2021 [5].

Our aim is to trace the changes that GDPR has brought to French services. However, before the analysis, we have to consider the state of web privacy practices before the GDPR legislation for a better overview. It allows us to capture early compliance efforts and anticipatory changes, highlighting proactive and reactive adjustments to the regulation. The end of the range is also significant due to the potential for enforcement actions and penalties for organizations.

Other interesting dates that we believe have affected the introduction of cookie dialogues are the sanctions given by CNIL to Google and Amazon [6] [7] [8]. These fines, amounting to tens of millions of euros, were among the first major penalties for non-compliance with GDPR regulations in France. They likely encouraged other service providers to improve their compliance efforts. The significance of these dates lies in their potential to act as triggers, affecting companies to swiftly update their websites to meet GDPR standards, thereby influencing the trend of cookie dialogue implementations.

Number of Websites. For this case study, we focus on analyzing 1,000 of the most popular French domains: This selection offers a representative sample of the French web, allowing for an in-depth analysis of cookie dialogue practices on these websites. Selecting 1,000 websites balances capturing a comprehensive range of data and managing the practical limitations of data processing. Considering the complexity and time involved in classifying cookie dialogues with the XLM-RoBERTa model, this sample size is manageable and sufficient to get valuable results.

[4] GDPR 679/16.
[5] CNIL regulation.
[6] Google 2019 fine by CNIL.
[7] Google 2020 fine by CNIL.
[8] Amazon 2020 fine by CNIL.

5.2 Experiment

This part is split into three phases: Website collection, Web elements retrieval and Classification of the elements.

Website Collection. The website collection process involves executing scripts to filter the Tranco list according to our predefined criteria, focusing on selecting the Tranco Top 1,000 websites for the French code top-level domain (ccTLD). The idea of this phase was to retrieve historical snapshots from the WayBack Machine. Using the WayBack Machine API, we accessed these snapshots on the service side, managing API data retrieval errors. It involved losing connection to the server or losing the record in the archive. The end of this phase was the organization and logging of successfully retrieved URLs into a structured JSON format.

Web Elements Classification. After successfully generating the URL list, we extracted and classified relevant web elements from these websites. Implementing automated web scraping, we navigated through each website, parsing HTML content to target *iframe* and *div* elements — the most likely containers for cookie dialogues. We then used the XLM-RoBERTa machine-learning model to classify this extracted data to identify the presence of cookie dialogues and determine the types of buttons included. Finally, we documented the classification results and stored them in a JSON format corresponding to each website.

5.2.1 Experiment Implementation

Below, we give a general pseudo-code for our implementation, illustrating the creation of a list of URLs and the Classification of Web Elements from these URLs. A more detailed specification of the WayBack API is given in Section 5.2.2.

Algorithm 1 Algorithm for creating a list of URLs

```
function FETCH_ARCHIVED_URLS(website, start_date, end_date, collapse_by, depth = 0)
    if depth > 1 then
        return ∅
    end if
    list_of_urls ← ∅
    reply ← WayBackAPI call to get URLs for website, start_date, end_date, collapse_by
    for each data_point in reply do
        try
            date ← extract date from data_point
            url ← extract URL from data_point
            list_of_urls.append((url, date))
        catch
            wait for 30 seconds
            return fetch_archived_urls(website, start_date, end_date, collapse_by, 1)
        end try
    end forreturn list_of_urls
end function
function GET_URLS()
    allWebsites ← Tranco API retrieve list for given date
    websites ← Filter allWebsites to end with .fr and to be of length of 1,000
    list_of_urls ← ∅
    for web in websites do
        list_of_urls[web] ← fetch_archived_urls(web, 2016-04, 2021-04, timestamp:6, 0)
    end for
    Save list_of_urls to json file
end function
```

Generating a list of URLs. The first part of our implementation process focuses on generating a comprehensive list of URLs from the Tranco list dated 2019-02-20.

1. **Tranco List Filtering**: From the extensive Tranco list, we filter out the Tranco Top 1,000 websites for our selected ccTLD - .fr.
2. **WayBack Machine API Usage**: Via *CDX waybackpy*, we access the WayBack Machine to find the closest historical record to our specified dates. The API attempts to retrieve a record for each date, moving to the next date with a specified step. If retrieval fails, the API continues attempts with the closest timestamp until successful.
3. **JSON File Creation**: For the ccTLD, we create a JSON file containing the successfully retrieved URLs within our date range, ensuring a structured and accessible dataset for analysis.

Algorithm 2 Help functions for for Classifying Web Elements

```
function CRAWL_URL(url_to_visit)
    try
        Visit url_to_visit using selenium
        Wait for wayback to redirect and website to load
        Get all text elements, buttons, iframes, divs
        Get all text and buttons elements from iframes and div with max depth 20 or time search 6 minutes
        Check for word "Cookie" in text and if found put it in the beginning of the list to check
        Check values for cookie dialogue
        if not cookie dialogue found then return "not found"
        end if
        Check for buttons for accept and decline return cookie dialogue, cookie buttons, "found"
    catch
        return "error"
    end try
end function
function COLLECT_WEBSITE_DATA(websites_to_crawl, dictionary_of_urls)
    for each web in websites_to_crawl do
        for each url_to_visit, date in dictionary_of_urls[web] do
            if dialogues_found ≤ 3 then
                Call crawl_url(url_to_visit)
                if found dialogue then
                    dialogues_found ← 0
                else
                    dialogues_found ← dialogues_found + 1
                end if
                if dialogues_found == 0 then
                    save a copy of results
                end if
                if found == "error" then
                    dialogues_found ← 0
                    Get value for web link to error
                end if
            else
                Break loop
            end if
        end for
        if not found a dialogue then
            Save "no dialogue found" for this website
        else
            Save all found dialogues
        end if
    end for
    return Save dialogues for all websites
end function
```

Algorithm 3 Algorithm for Classifying Web Elements

Part 2: Classifying Web Elements
dialuge_model, button_model ← TRAIN XLM-RoBERTa model on dataset for dialogue and button classification
Load list of website and their links to visit from json to urls_to_visit
Get websites_to_visit from urls_to_visit
Reverse links to visit in urls_to_visit
collect_website_data(websites_to_visit urls_to_visit)
STORE classification results in JSON file for URL

Classifying Web Elements. The second part involves classifying web elements using the XLM-RoBERTa machine learning model, focusing on identifying cookie dialogues and their corresponding buttons on the web pages:

1. **Model Training**: Initially, we train the XLM-RoBERTa model on a dataset comprising 650 entries for dialogue classification and 1,150 for button classification, covering all EU languages.
2. **Web Page Parsing**: With Selenium WebDriver in headless mode (browser windows are not visible), we process each URL from our JSON files, parsing the HTML to locate "iframe" and "div" elements that potentially contain cookie dialogues. We recursively go through these elements (because "iframe" might have "iframes" inside and so on) until we visit them all or we have reached the *depth 10* from the initial element.
3. **Elements Classification**: We extract text from these web elements, relying on the XLM-RoBERTa model to classify whether a cookie dialogue is present.
4. **Button Classification**: If the model determines the presence of cookie dialogue, it extracts the text content of potential buttons and classifies them.
5. **Misclassification Handling**: It performs one more iteration on the next date, and if it also contains a cookie dialogue, stop the iteration for this website. This way, we ensure it was not a misrecognition and that a cookie dialogue has indeed been added to the website at the spotted date. Otherwise, we continue analyzing with the next date.
6. **Output Compilation**: The final step involves compiling the classification results into a JSON file for each URL, documenting the dates and text of identified cookie dialogues and buttons.

The data range is examined in a reverse descending order - from April 2021 to April 2016. That serves our purpose better because of an assumption that most web services do not tend to adapt to the regulations in the first half of the specified period. Hence, we can save time by looking for a "disappearance" of a cookie dialogue and buttons rather than appearance. Additionally, we omit potential dialogues with a text length shorter than 125 characters, as they may not comply with GDPR requirements simply because it is too short to fit the required content.

5.2.2 WayBack Implementation Specification

To discuss the choice of a day we are going to check for every month, we need to point out that from the WayBack side, the CDX Server's function:

```
WaybackMachineCDXServerAPI(url=website, user_agent=USER_AGENT,
    start_timestamp=start_date, end_timestamp=end_date, collapses=[
    collapse_by])
```

where the parameter *collapse_by* allows us to adjust the frequency of a check, it is limiting our choice of step size to three options: once a month, once every 10 days - 01, 10, 20, 30 of a month, and once a day. What is also important to note is that upon requesting the URLs of a specified date, the API would return the succeeding closest date. For example, if the specified timestamp is for every month, then the API will attempt to return the earliest available URL of the 1st of the month. That should not affect the results and the experiment flow as long as we keep it in mind.

We will use the Selenium WebDriver package to perform the URL retrieval to access and manipulate web content, observing pages in headless mode. The WayBack server may refuse connections due to excessive requests, so that we will use the *driver.wait()* function to avoid overloading the server.

5.2.3 Foreseen limitations

Certain limitations may affect the outcomes of the experiment. It is important to be aware of these limitations upon interpreting the results:

- Due to the time complexity of this task, the study focuses on 1,000 selected websites in France. It might lead to a partially accurate representation of the internet landscape in France at that time. However, it should provide a confident insight.
- Multiple popular websites on the EU territory do not use EU ccTLD (e.g., bol.com) but still follow the GDPR guidance. At the end of this research, the presented data will not give an ultimate insight but will provide a general idea.
- The WayBack machine does not keep records of each website for any given day. For example, if a website has implemented a cookie dialogue on the 31st, but the WayBack only kept a copy of the 30th and the 2nd of the next month, the output will be the date of the following month. The results will contain a few weeks' error but will still be sufficient for our research question.
- The study's reliance on the earliest available Tranco list from 20-02-2019, instead of the initially intended 01-06-2018 list, presents a limitation regarding immediate post-GDPR most popular websites analysis and reproducibility. This gap might affect the ability to fully replicate or extend the study with data from the initial aftermath of the GDPR implementation.
- Due to the time feasibility, the crawler runs in headless mode - without displaying the interface and hence using fewer resources - which can potentially alter the web elements to the point a cookie dialogue might not show [KJK22].

Considering the limitations of the WayBack API, we expect a margin of flexibility of available URLs of approximately 10%, allowing us to account for missing URLs while still maintaining the total sample of 1,000 websites with 61 URLs each, one for each month in the time period.

5.3 Results

In this section, we present the results of our experiment creating timeline to track cookie dialogue evolution.

5.3.1 Results for Identifying Cookie Dialogues

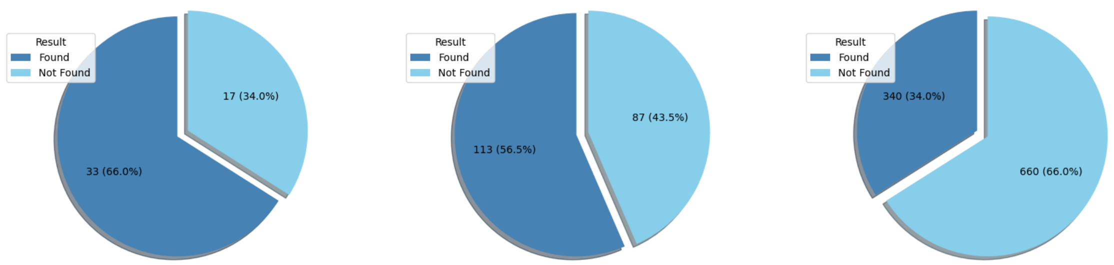
Presence of Cookie Dialogues

We observed the Tranco Top 50, Top 200, and Top 1,000 most popular websites in France over the five years to assess the presence of cookie dialogues. The findings are summarized in Figure 5.1, which categorizes the results into two groups: websites where a cookie dialogue was found and those where it was not.

To be classified as a website with a cookie dialogue, the following criteria were applied:

- The potential cookie notice text length must exceed 125 characters.
- The content must be classified as a cookie notice by the XLM-RoBERTa model.

For the Tranco Top 50 websites, 66% were identified as having a cookie dialogue, while 34% did not. In the Top 200 websites, 56.5% were found to have a cookie dialogue, with 43.5% falling into the Not Found category. Among the Top 1,000 websites, 34% had a cookie dialogue, and 66% did not.



(a) Presence of cookie dialogues in Top 50 Websites.

(b) Presence of cookie dialogues in Top 200 Websites.

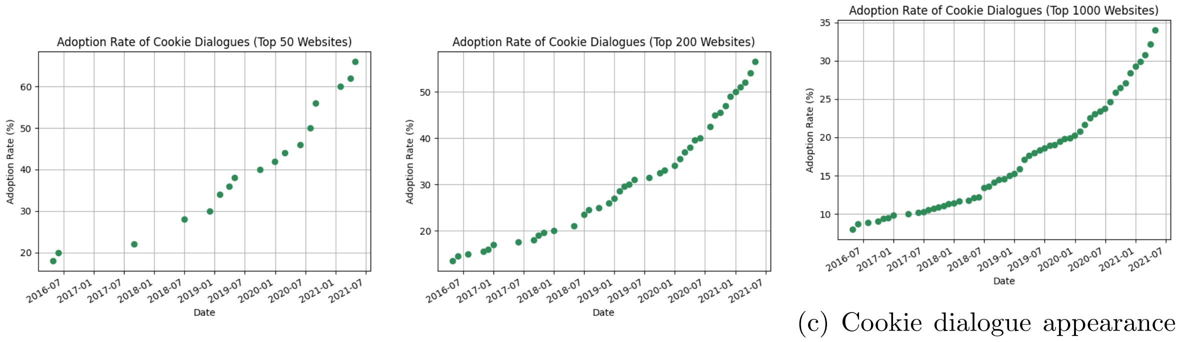
(c) Presence of cookie dialogues in Tranco Top 1,000 Websites.

Figure 5.1: These pie charts illustrate percentages of identified and unidentified cookie dialogues for Top 50, 200 and 1,000 websites.

Adoption Rate

Figure 5.2 presents the adoption rates to cookie dialogue regulations in the Top 50, Top 200, and Tranco Top 1,000 most popular websites for five years.

In the Tranco Top 50 Websites, the adoption rate begins at around 20% in mid-2016 and steadily increases to over 60% by mid-2021, showing a consistent rise with significant increases post-2018. In the Top 200 Websites, starting at around 15% in mid-2016, the rate gradually climbs to approximately 55% by mid-2021. For the Top 1,000 Websites, the rate starts at around 10% in mid-2016 and reaches about 35% by mid-2021.



(a) Cookie dialogue appearance rate in Top 50 Websites.

(b) Cookie dialogue appearance rate in Top 200 Websites.

(c) Cookie dialogue appearance rate in Tranco Top 1,000 Websites.

Figure 5.2: These scatter plots illustrate the cookie dialogues implementation rate for Top 50, 200 and 1,000 websites.

Response Time

Figure 5.3 illustrates the response time to GDPR guidelines regarding cookie dialogues for Tranco Top 1,000 Websites. The cookie dialogues implemented before the five year period come up to 10%, the Period 3 accounts for the most common response time of 21.5% with the Period 4, 5 and 6 accounting for 18%, 17.6% and 19.7%.

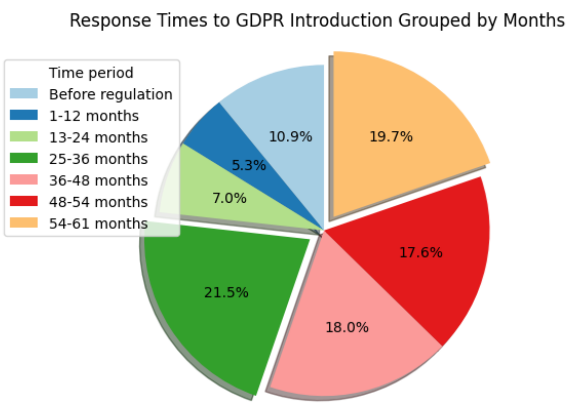


Figure 5.3: This pie chart demonstrates the response times of Tranco Top 1,000 Websites to GDPR guidelines.

Timeline for cookie dialogue evolution in France

We observed the 1,000 most popular domains in France, dated February 20, 2019. Each website has been checked monthly for five years to spot the first appearance of a cookie dialogue in Tranco's Top 50, Top 200, and Top 1,000 most popular websites. The data is represented bimonthly per number of websites that introduced a cookie dialogue that month. GDPR and CNIL legislation and the most significant sanctions within that period were added. The results are summarised in Figure 5.4.

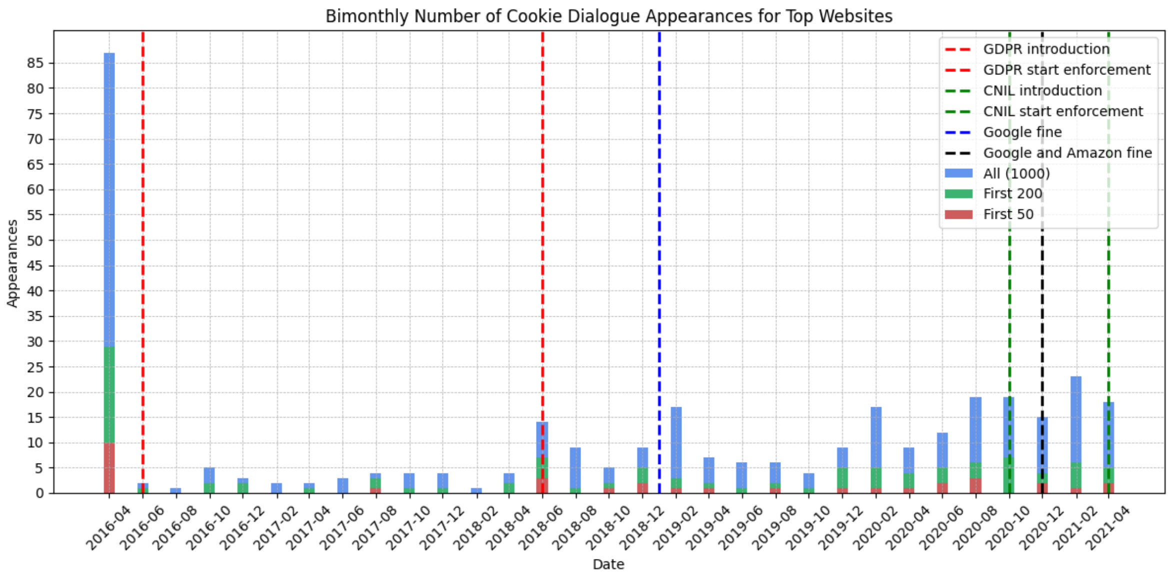
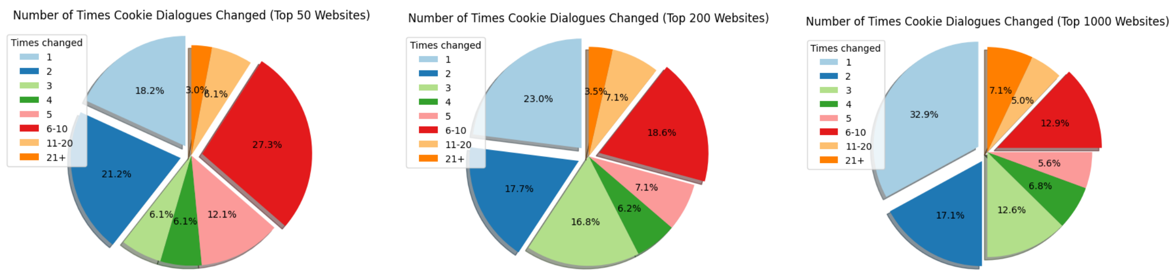


Figure 5.4: This stacked bar chart represents the timeline of cookie dialogues first appearances over the period of 5 years including the dates of legislative events in France.

5.3.2 Results for Tracking Changes in Cookie Dialogues

The pie charts in Figure 5.5 present the distribution of how many times the cookie dialogues changed on the Tranco Top 50, 200, and 1,000 websites with an identified cookie dialogue over the five years.

For the Top 50 websites, the majority, 27.3%, changed their cookie dialogues between 6 to 10 times, followed by 21.2% that changed it twice, and 18.2% changed it only once. The least frequent category was those changing their cookie dialogues more than 21 times, which accounted for 3.0%. In the Top 200 websites, 23.0% of them changed their cookie dialogues only once, and 18.6% of the websites changed their cookie dialogues between 6 to 10 times. Notably, 3.5% of websites changed their cookie dialogues over 21 times. In the Tranco Top 1,000 websites, 32.9% changed their cookie dialogues only once. A smaller percentage, 17.1%, changed their dialogues 2 times, while 12.9% of websites updated their dialogues between 6 to 10 times. Very few websites, only 5.0%, updated their cookie dialogues more than 21 times.



(a) Times cookie dialogues changed for Top 50 Websites.

(b) Times cookie dialogues changed for Top 200 Websites

(c) Times cookie dialogues changed for Top 1,000 Websites

Figure 5.5: These pie charts illustrate how many identified cookie dialogues changed over five year period for Tranco Top 50, 200 and 1,000 websites.

Figure 5.6 illustrates the changes in cookie dialogue lengths between the first and last occurrences, showing data only for websites that have changed their cookie dialogues at least twice. We filtered out values above 1,500 characters to enhance readability. For the Top 50 websites, the length difference varied up to 500 with a median of 200 characters, and one outlier was detected; for the Top 200 websites, it varied up to 400 with a median of 150 characters, there were two outliers; and for the Top 1,000 websites, the range was up to 250 with a median of 100 characters while three outliers were present.

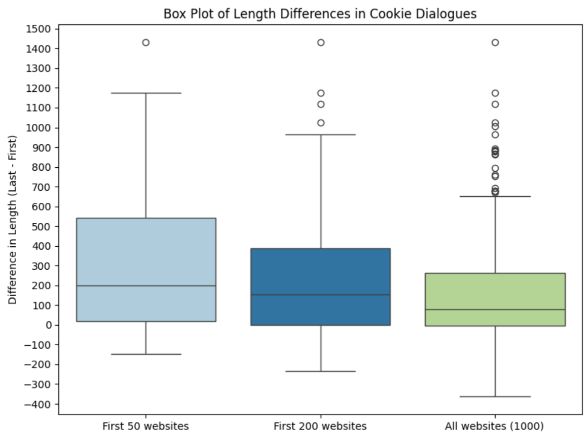


Figure 5.6: This box plot demonstrates the distribution of cookie dialogue length difference between first and last occurence for the list of Tranco Top 50, Top 200 and Top 1,000 websites.

5.4 Analysis

The results of our cookie dialogue appearance and evolution experiment, as described in section 5.3, show the effects of the GDPR and CNIL regulations on the French websites. In this section, we will discuss the implications of these findings.

Analysis of Presence of Cookie Dialogues

The results reveal a clear trend in adopting cookie dialogues among popular websites in France over five years. Most Tranco Top 50 websites (66%) implemented cookie dialogues, likely due to their higher visibility and increased scrutiny from regulatory bodies. However, as the list expands to the Top 200 and Top 1,000 websites, the proportion of sites with detectable cookie dialogues decreases from 56.5% to 34%. That suggests that smaller or less popular websites may not exactly prioritize GDPR and CNIL compliance, highlighting a potential compliance gap.

Analysis of Adoption Rate

For the Tranco Top 50 websites, the adoption rate steadily increases from approximately 20% in mid-2016 to over 60% by mid-2021. This trend suggests a consistent adoption of cookie dialogues among the most popular sites, likely driven by enforcing GDPR and subsequent CNIL regulations. In the case of the Top 200 websites, the adoption rate shows a similar upward trajectory but at a slower pace, reaching just over 50% by mid-2021. That indicates a broader but slightly delayed implementation of cookie dialogues across various popular websites. For the Top 1,000 websites, the adoption rate begins at around 10% in mid-2016 and gradually climbs to approximately 35% by mid-2021. This slower adoption rate among a larger pool of websites suggests that smaller or less trafficked sites may have been slower to implement cookie dialogues due to fewer resources or a perceived lower risk of regulatory punishment.

Analysis of Response Time

The most significant portion, 21.5%, represents websites that adjusted their cookie dialogues 13-24 months after the GDPR's introduction. The period just before the GDPR's enforcement caught 19.7% of websites implementing changes, highlighting a proactive approach by some services. However, 18.0% and 17.6% of websites only adjusted their practices 25-36 and 36-48 months post-GDPR, indicating a delayed compliance response. A smaller fraction, 7.0%, made changes in the earlier 1-12 months post-GDPR. At the same time, only 5.3% took action before the regulation took effect, showing different levels of urgency across various websites. These findings suggest a significant delay in overall compliance with GDPR, with nearly half of the websites taking more than two years to adapt to regulatory requirements.

Analysis of Timeline

The data reveals several distinct periods of increased cookie dialogue appearances. Notably, there was a significant spike in the number of appearances around the time of the GDPR enforcement in May 2018. This spike is most noticeable across all three groups of websites, indicating a significant push towards compliance following the regulation's enforcement. The following spikes correspond to CNIL's introduction and enforcement of specific guidelines in late 2020 and early 2021. Notably, the fines imposed on Google and Amazon in December 2020 appear to have influenced another wave of cookie dialogue implementations, as seen by the sharp increase in appearances during this period. The pattern of spikes following significant regulatory actions suggests a reactive approach among many websites, where compliance is primarily driven by the introduction of new regulations or the threat of enforcement rather than proactive measures. Overall, this graph highlights the strong influence of regulatory actions and enforcement on adopting cookie dialogues across popular websites in France.

Analysis of Number of Cookie Dialogue Changes

The analysis reveals that more popular websites like the Tranco Top 50 frequently updated their cookie dialogues, indicating a commitment to regulatory compliance. This behavior is likely driven by their high visibility and the higher chance of legislative prosecution. In contrast, as we move to the Top 200 and Top 1,000 websites, the frequency of updates decreases, suggesting that less popular websites may not have the same resources or incentives to stay as up-to-date. That indicates a more reactive approach to compliance among smaller websites and highlights the need for increased support and awareness to ensure broader adherence to privacy regulations.

Analysis of Cookie Dialogue Length Changes

We observe a consistent pattern where, on average, websites increased the length of their cookie dialogues. The interquartile range across all categories (Top 50, Top 200, and Top 1,000 websites) indicates that cookie dialogues grew in complexity, likely due to evolving legal requirements and greater transparency. The presence of a few outliers suggests that some websites made significant changes, possibly as a reaction to specific compliance actions or penalties. The differences are more visible in the smaller datasets (Top 50 and Top 200), indicating that the most popular websites may have adapted faster or more dramatically than the broader selection.

5.5 Validity

Despite the capabilities of the XLM-RoBERTa model and the archival data from the WayBack Machine, classification discrepancies such as false positives (instances where non-cookie dialogues were incorrectly classified as cookie dialogues) and false negatives (actual cookie dialogues that were missed by the classification) were encountered. We performed manual checks on the data selected by bootstrap sampling to confirm or refute its classifications. We have checked 400 websites with resampling from the list of one thousand. Through this verification, we could spot misclassifications and errors and get an insight into how well our implementation performs.

5.5.1 Verifying WayBack API

The WayBack API successfully retrieved records for 980 out of the 1,000 websites. Upon reviewing the number of URLs generated per website, only 33% of the websites reached the desired count of 61, as illustrated in Figure 5.7. Due to limitations of the WayBack API, several websites fell short of this target. To be more specific, we retrieved 51,991 URLs from the WayBack API out of the expected 61,000, which accounts for 85.23%. As we mentioned in the foreseen limitations in Section 5.2.3, we expected the margin of flexibility of 10%. However, the actual margin that we observed is 14.8%. Although it exceeds the original margin, we consider it reasonable because we are investigating 1,000 French websites.

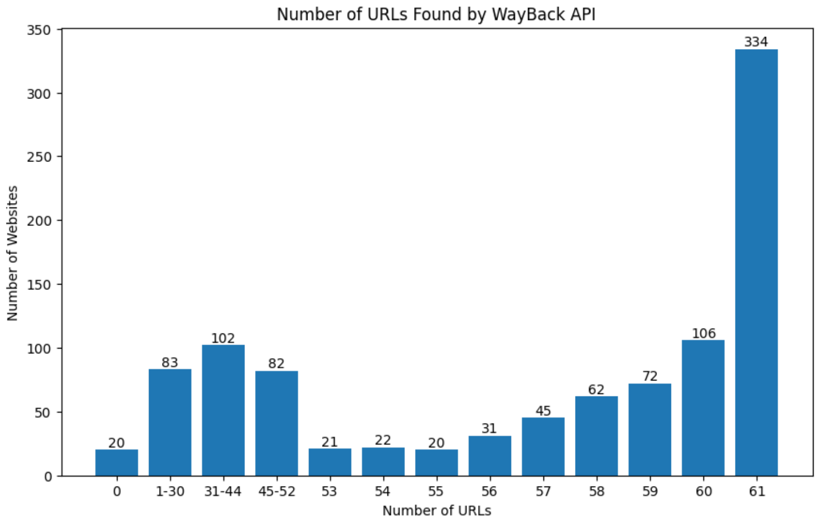


Figure 5.7: This graph show the distribution of the number of URLs obtained by WayBack API.

5.5.2 Verifying the Method with Bootstrapping

To evaluate the accuracy of the implemented methodology, we performed a bootstrapping approach across three lists of websites, with sample sizes of 40, 100, and 250. We assessed the accuracy of two key components: identifying the date of the first occurrence of a cookie dialogue and recognizing the content of the dialogue. Although the accuracy of detecting the first occurrence is dependent on correctly identifying the cookie dialogue content, it is critical to separate the results of our XLM-RoBERTa model from our crawler's performance.

For this purpose, we categorized data into two categories: **Dialogue Present** for websites that end up having a cookie dialogue on their page, and **No Dialogue** for websites with no cookie dialogue. While only **Dialogue Present** case was evaluated, the **No Dialogue** results showed near-perfect accuracy across all datasets, with almost no misclassification. As a result, we focus on presenting the model's accuracy for **Dialogue Present** cases, where there is more variability and a need for deeper analysis. That allows us to highlight the areas where the system may require further improvement.

Figure 5.8 represents the accuracy distribution for websites with cookie dialogue, broken down into **Correct Date**, which stands for correctly identifying the date of the first occurrence of one and **Correct Text** that stand for correctly recognizing the content of a dialogue. The graph displays results from different sample sizes used in the bootstrapping analysis, allowing for a clear comparison across datasets.

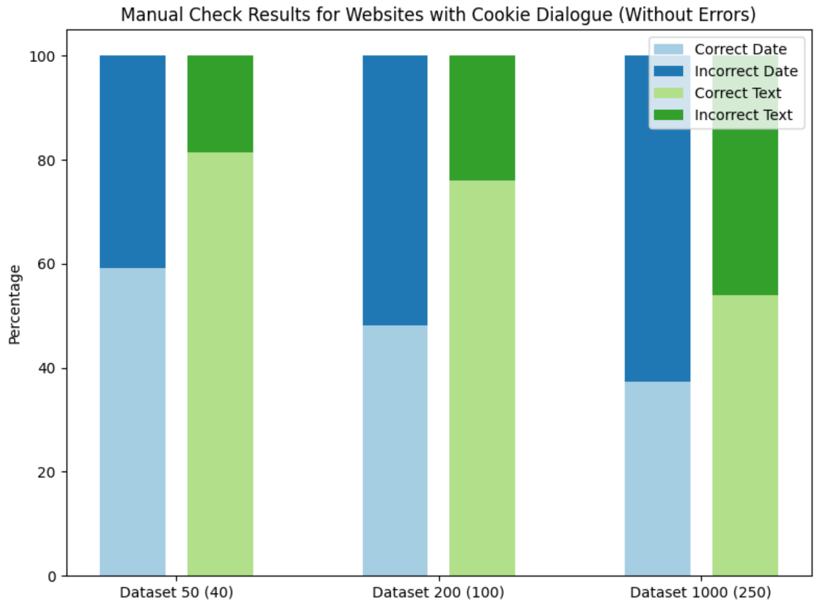


Figure 5.8: These bar charts represent the results of manual checks for three data sets on websites with a cookie dialogue without Errors.

These findings are summarized in Table 5.1 for a clearer overview. As the number of websites checked increases, the accuracy of identifying the correct date steadily declines: from nearly 59.5% for the Tranco Top 50 websites to 37.5% for 1,000 websites. A similar pattern is observed with correct text recognition, dropping from 81.5% to 54%. This decline is likely cause by complex design of web elements on less popular websites, making it more difficult for the crawler to identify cookie dialogues accurately.

Table 5.1: Correct Date and Correct Text (Dialogue Present)

Sample Size	**Correct Date (Dialogue Present)**	**Correct Text (Dialogue Present)**
40 (List of 50)	59.26%	81.48%
100 (List of 200)	48.14%	75.92%
250 (List of 1,000)	37.39%	53.91%

Furthermore, we observed discrepancies in how changes in cookie dialogue content were tracked. In 18 instances, changes in the website's structure led to a misclassification. For example, a single cookie dialogue was split into two distinct web elements that were evaluated independently by the crawler. This design modification resulted in incomplete records of cookie dialogues, with the crawler incorrectly marking these instances as content changes.

- **General Accuracy of Correct Date:**

$$\text{Accuracy} = \frac{\text{Correct Date (Dialogue Present)} + \text{Correct Date (No Dialogue)}}{\text{Sample size without errors}} \times 100$$

- **General Accuracy of Correct Text:**

$$\text{Accuracy} = \frac{\text{Correct Text (Dialogue Present)} + \text{Correct Text (No Dialogue)}}{\text{Sample size without errors}} \times 100$$

To compute the method's accuracy, we have taken both **Dialogue Present** and **No Dialogue** results of the manual check. That allowed us to evaluate the accuracy of the method performance on three data sets as shown in Table 5.2. The accuracy of, on average, 68.18% was shared between all data sets for correctly specifying either the date of the first dialogue occurrence or the absence of one in case of no dialogue. Undoubtedly, the second case has increased the general accuracy compared to Table 5.1 but still shows promising results for avoiding false negatives. We also see this effect on the accuracy of cookie content text recognition, which for the list of 50 and 200 websites is on average 85.29%, compared to 76.85% for the list of 1,000.

Table 5.2: General Accuracy and Error Rate

Sample Size	**General Accuracy (Correct Date)**	**General Accuracy (Correct Text)**	**Error Rate**
40 (List of 50)	68.57%	85.71%	12.5%
100 (List of 200)	67.44%	84.88%	14%
250 (List of 1,000)	68.55%	76.85%	8.4%

5.6 Discussion

In this case study, we used our proposed methodology to get a practical understanding of how efficiently it works and where it might fall short. In this section, we discuss what our findings suggest, the limitations we encountered, and possible improvements.

The results show that our methodology can successfully point to connections between major data protection events, like GDPR enforcement, and cookie dialogue changes. The results also give insight into how websites adapt to new data protection rules and suggest how we might measure the broader influence of these regulations on data privacy practices.

However, we have encountered several limitations that affected data accuracy. For example, inconsistencies in WayBack Machine API snapshots and issues with JavaScript content not fully loading reduced data reliability. To address these limitations, we could consider methods to avoid headless browser crawling. Anti-bot measures on some websites also prevented us from accessing essential content. A more sophisticated scraping approach could be implemented to increase data integrity and readability.

Additionally, we noticed issues with missing records on less popular websites. Filtering out sites with incomplete records could improve accuracy. However, it may reduce the sample size.

The implementation failed to classify cookie buttons such as *Reject All* and *Accept All* due to isolated analysis of web elements and reliance on the Machine Learning model, suggesting an advanced combination of these two methods.

Lastly, we discovered a trade-off between processing time and depth of the analysis. One way to mitigate this limitation is to increase the search depth to improve element capture; however, it would extend processing time. Balancing these factors is a necessity to optimize the methodology for future use.

Chapter 6

Conclusion

The goal of this thesis was to develop a scalable methodology for tracking the evolution of cookie dialogues in response to data protection regulations. The idea was to create an automated, multi-lingual approach capable of analyzing large datasets over time.

Through the case study of French websites, this research has demonstrated how these dialogues have adapted to comply with regulations like the GDPR and CNIL. By leveraging the WayBack Machine and the XLM-RoBERTa classification model, this study successfully captured patterns and trends in cookie dialogue adoption, demonstrating how data privacy practices evolve due to regulatory pressures.

The findings highlight the correlation between enforcement events—such as GDPR implementation and subsequent fines — and the timing of cookie dialogue adoption. That suggests that major regulatory events influence significant changes in compliance behavior. However, the study also reveals the variability in adaptability levels across websites, with more popular domains adapting more quickly than less popular sites.

Despite these insights, the study encountered several limitations. Issues with accurately classifying cookie dialogues and variations in website structure presented challenges. These limitations suggest further improvement of the crawling and classification methods, particularly to improve accuracy in identifying and categorizing cookie buttons and dialogue structures. The study also reveals the constraints of the WayBack Machine's archival quality and access restrictions.

In conclusion, this thesis's main contribution to longitudinal studies on cookie dialogues offers a scalable approach for examining how data protection regulations influence online privacy practices. Future work could improve this methodology by addressing the identified limitations and exploring more diverse datasets for a broader understanding of privacy compliance trends across different regions and regulations. By adjusting these tools, researchers can continue to monitor and analyze the evolving field of user privacy in the digital age.

Future Work . We believe future work can enhance cookie dialogue analysis through several key improvements. First, refining the classification model to more accurately identify specific cookie button types, such as "Accept All" or "Reject All," would significantly increase precision. That could involve fine-tuning XLM-RoBERTa or exploring other models trained on diverse cookie dialogues.

Expanding the dataset to include a broader range of websites, including smaller businesses and less popular sites, would provide a broader view of compliance trends. Analyzing websites across multiple EU countries would also help highlight regional variations in GDPR and local DPA enforcement. Moreover, improving web crawling methods, such as handling dynamic content more effectively, would enhance data accuracy.

Lastly, future studies could explore the application of this method for different tasks and deepen our understanding of digital privacy and the effectiveness of data protection laws.

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Appendix A

Legislative Timeline

The purpose of this appendix is to present a constructed timeline highlighting the critical legislative records and authoritative decisions shaping the discussion around cookie consent in France.

Our timeline starts with the ePrivacy Directive (ePD), an early legislative effort to address privacy concerns in the digital environment, particularly focusing on informed consent for cookies. Although our research does not involve investigating for this period, understanding the ePD provides context for subsequent regulations. Moving forward, we examine the General Data Protection Regulation (GDPR), a comprehensive set of laws that changed how personal data can be used and issued specific rules regarding cookie consent more explicitly. This regulation significantly impacted cookie consent mechanisms, necessitating redesigns of consent interfaces to comply with stricter requirements. Lastly, we explore a significant decision by the French Data Protection Authority (CNIL) in September 2020, which refined standards around cookie consent mechanisms in France.

Unimplemented 2019 CNIL Legislation on "Reject All" Option
In 2019, the French Data Protection Authority (CNIL) proposed legislation that mandated a "reject-all" option for cookies, aiming to enhance user consent autonomy and ensure that rejecting cookies was as straightforward as accepting them. This proposal was designed to fully align with the General Data Protection Regulation (GDPR) principles of clear and affirmative consent. However, the legislation never came into effect, possibly due to pushback from industry stakeholders or challenges related to practical implementation [1]. This example underscores the dynamic nature of regulatory efforts in digital privacy and highlights the complexities involved in enforcing such laws.

As we have seen, the journey of digital privacy regulations within France has been marked by continuous adaptations and enhancements aimed at strengthening user consent mechanisms. However, not all proposed changes have been straightforward to implement.

[1] CNIL revised cookie guidelines.

Legislation	Details
ePrivacy Directive (ePD)[2]	• **Date of Directive:** 25 November 2009 • **Legislation:** Directive 2009/136/EC (amending Directive 2002/58/EC) • **Implementation Deadline for EU States:** 25 May 2011 • **Key Requirement:** Introduction of informed consent for cookies, differentiating between required and optional cookies. • **Impact and Insufficiencies:** – Mandated informed consent for cookies, especially those not strictly necessary for service delivery. – Vague definitions of consent led to variable interpretations among EU countries. – France initially adopted a lenient interpretation, where continued browsing was often seen as consent. – This approach was criticized for not offering a genuine choice and potentially overstepping privacy rights. – Resulted in inconsistent implementation across EU member states.
General Data Protection Regulation (GDPR) [3]	• **Date of Regulation:** 25 May 2018 • **Legislation:** Regulation (EU) 2016/679 • **Adaptation Period:** Two-year transition period from adoption on 27 April 2016. • **Key Requirement:** Specification of requirements for active and informed consent. • **Impact and Insufficiencies:** – Introduced a strict definition of consent—freely given, specific, informed, and unambiguous. – Required extensive redesigns of cookie consent mechanisms to comply with new requirements. – Posed challenges for many businesses in France, struggling to balance user experience with legal compliance. – Initial compliance efforts varied widely, reflecting the broad impact and significant adjustments required by GDPR.
CNIL Rulings [4]	• **Date of Regulation:** September 2020 • **Legislation:** Ruling by the French Data Protection Authority (CNIL) • **Adaptation Period:** Implementation required by 31 March 2021 • **Key Requirement:** Mandate of a "reject-all" option for cookies, alongside an "accept-all" option, and prohibition of cookie walls. • **Impact and Insufficiencies:** – Addressed the imbalance in cookie consent mechanisms by mandating a "reject-all" option. – Enhanced user autonomy and privacy by making it as easy to refuse cookies as to accept them. – Posed technical and design challenges for website operators in implementing compliant cookie consent interfaces. – Clarified expectations for consent mechanisms, promoting user-centric consent processes.

Table A.1: Timeline of Major French Legislative Developments Impacting Cookie Dialogues

[2] ePD 2009.
[3] GDPR 679/16.
[4] CNIL regulation.