



# "You Don't Need a University Degree to Comprehend Data Protection This Way": LLM-Powered Interactive Privacy Policy Assessment

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## Abstract

Protecting online privacy requires users to engage with and comprehend website privacy policies, but many policies are difficult and tedious to read. We present the first qualitative user study on Large Language Model (LLM)-driven privacy policy assessment. To this end, we build and evaluate an LLM-based privacy policy assessment browser extension, which helps users understand the essence of a lengthy, complex privacy policy while browsing. The tool integrates a dashboard and an LLM chat. In our qualitative user study (N=22), we evaluate usability, understandability of the information our tool provides, and its impacts on awareness. While providing a comprehensible quick overview and a chat for in-depth discussion improves privacy awareness, users note issues with building trust in the tool. From our insights, we derive important design implications to guide future policy analysis tools.

## CCS Concepts

• **Security and privacy** → **Human and societal aspects of security and privacy**; • **Human-centered computing** → *Empirical studies in HCI*; *Web-based interaction*.

## Keywords

Privacy, Privacy Enhancing Technologies, Computer-Human Interaction

## ACM Reference Format:

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## 1 Introduction

Almost every interaction with companies, online services, smart devices, etc. leaves trails of personal data. Companies leverage techniques like hyper-personalization, powered by Artificial Intelligence (AI) and Machine Learning (ML) with real-time data sources [24], to create user profiles and enable micro-targeting [7]. This results in vast privacy risks, such as automated influence [5], manipulation [31], and potential security breaches. While companies invest in acquiring and analyzing their users' personal data, users often lack awareness of the associated privacy risks [15] or have distorted perceptions of them [16]. Privacy regulations such as the GDPR [13] force companies to communicate data management practices and users' rights in *privacy policies*, thereby empowering users to make informed decisions about their personal information. However, evidence shows that companies focus on compliance, targeting lawyers instead of users [45], so users rarely read privacy policies [35]. Using LLMs to automatically assess privacy policies is a promising approach to solve this issue [20, 43, 53]. Yet, no prior work evaluates their impact on the user's understandability and risk awareness. Therefore, we conducted a scenario-based qualitative user study. It involved 22 participants from diverse backgrounds, acquired via different channels. To conduct this study, we developed a Chrome extension, PRISMe (Privacy Risk Information Scanner for Me), which combines LLM-based automatic privacy policy assessment with: (i) an interactive dashboard; and (ii) a chat for open conversations with the LLM with (iii) customizable explanations and responses that adapt to the user's preferences for detail and complexity. We focus on three research questions:

- RQ.1** How do users with varying privacy knowledge interpret PRISMe's privacy policy explanations?
- RQ.2** How does using PRISMe shape users' awareness of privacy risks?
- RQ.3** How suitable and usable is PRISMe for everyday use across different user contexts and tasks?

Our findings suggest that a tool such as PRISMe can tremendously help users who lack awareness and comprehension regarding online-privacy risks [16], by communicating relevant privacy protection information. Moreover, users tend to request evidence for the provided information (which PRISMe can provide).

Our **main contribution** is a qualitative user study evaluating LLM-based privacy policy analysis. Our findings mark an important step toward developing interactive tools that enhance privacy awareness and informational sovereignty.

## 2 Related Work

### 2.1 Challenges with Privacy Policies

Privacy policies aim to mitigate the *information asymmetry* between service providers and users [30, 55]. However, they are often designed for legal compliance, with dense, lawyer-centric language [45]. This makes it difficult for users to match them with their preferences [32, 52]. Legal regulations, e.g., GDPR [13] or [6], do not prevent persuasive language, which might obscure unethical practices and create a false sense of trust [4, 39]. Thus, users reading and understanding privacy policies is rare [41, 47], which results in informational unfairness [14]. Generative AI [29] and Augmented Reality complicate data management practices further and exacerbate transparency issues [2–4].

### 2.2 The Landscape of Transparency-Enhancing Technologies

Early *approaches reliant on a privacy language representation of the policy* like Privacy Bird [12], relied on the P3P privacy language [11] to preconfigure privacy sensitivity levels and used static, rule-based risk assessments to display warnings via a traffic-light system. Current privacy nutrition labels [25] provide a similar visualization. However, fixed criteria limit adaptability, and the lack of user-query mechanisms hinder interactivity and education. Inspired by these, PRISMe evaluates policies in the background and presents results succinctly. Grünwald et al. [18] later introduced layered dashboards with chatbot interaction but with limited dialogue flexibility. We also present minimal information initially, allowing users to uncover additional details based on chat interactions.

Tools like Poli-see [19] and ToS;DR [44] *rely on processed data*, e.g., crowd-sourced annotations. Poli-see visualizes data flows via icons on dashboards, while ToS;DR uses color-coded summaries for quick evaluation. Although effective at simplifying complexity, reliance on static data limit its scalability and adaptability.

Advances in *automated assessment with Natural Language Processing (NLP)* shifted focus to plain-text privacy policies. Polisis [21] and PriBot [22] utilized privacy-specific embeddings and ML classifiers to identify policy elements, allowing users to query content. Since the returned segments are direct policy quotes, users may still struggle with comprehension. In contrast, our LLM-based chat can deliver clearer explanations, cite policy evidence upon request, and handle a broader range of questions beyond the policy text. PrivacyInjector [52] enhanced decision-making through context-aware visualizations and explanations. While promising to improve privacy awareness, users suggested reducing text length and interpreting the severity of privacy threats, which PRISMe makes possible. PrivacyCheck [34] evaluates privacy policies using 20 static questions on user control and GDPR, 17 of them yes/no questions, scored by ML models. It identifies the website's market sector and compares scores with three competitors. However, its fixed questions and binary responses limit user interaction and the ability to query or simplify explanations.

Tools based on *ML classifiers*, e.g., Claudette [8], PrivacyGuide [50] and GDPR-completeness classifiers [1, 51, 54] evaluate binary or check-list-based scores on GDPR compliance. However, they often fail to communicate implications effectively to non-lawyers and do not consider individual privacy preferences.

*LLM-based privacy policy assessment* has shown to be as effective as NLP methods in extracting key aspects from privacy policies, such as contact information and third parties [43]. ChatGPT-4 offers performance and adaptability in answering privacy-related questions [20], which motivated our use of GPT-4o [36]. Privacify [53] is a browser extension summarizing policy chunks for compliance analysis and data collection insights. However, it lacks customization, interactive features, and, most importantly, a comprehensive evaluation.

### 2.3 Identified gaps for AI tools assessing privacy policies

Since *machine-readable privacy policy representations* are rare, tools like Privacy Bird offer inspiration but lack real-world applicability. Tools relying on *processed crowd-sourced data* face scalability and adaptability challenges. *Compliance-focused approaches*, while valuable for legal experts, struggle to address typical users. *Static criteria* limit adaptability to users' needs and evolving practices, and the *lack of interaction* in many tools hinders user engagement, awareness and comprehension. LLM-based tools remain nascent, with no qualitative user studies conducted.

## 3 Study Methodology

We conducted an exploratory lab-based qualitative user study (N=22) using a research prototype of PRISMe in three scenarios. We outline our scenarios first (full user instructions in Appendix A.2), and explain PRISMe in Section 4. Participants could spend as much time as they wanted in each scenario.

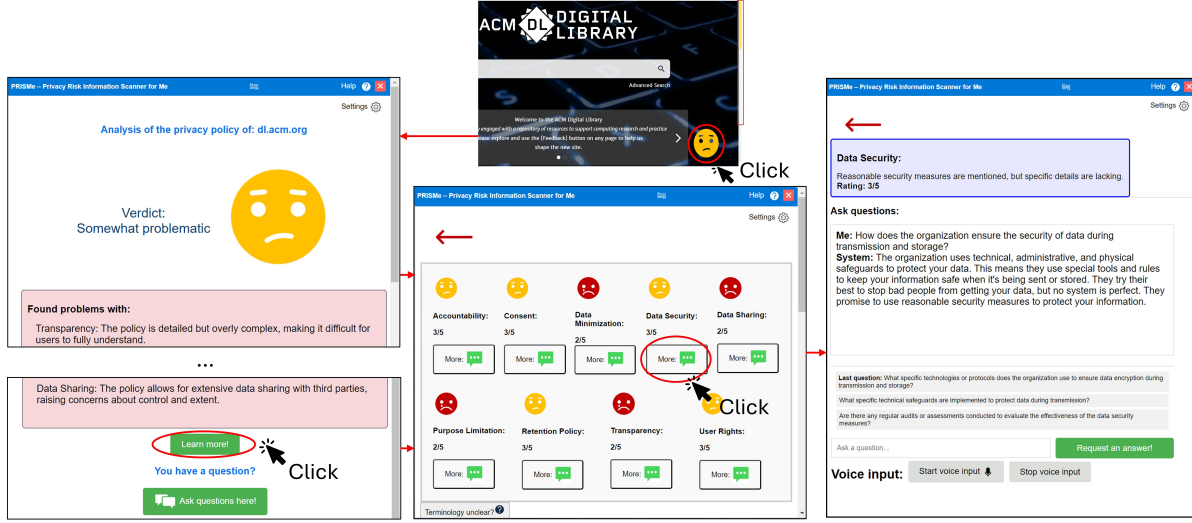
**Scenario 1 "Privacy Exploration on a News Media Platform (focus.de) and Payment Provider (PayPal)"** allows to assess how users engage with privacy policies using PRISMe, targeting **RQ.1** (*understanding*) and **RQ.2** (*awareness*). It exposes participants to common yet complex services with significant data collection.

**Scenario 2 "Comparing Privacy Practices"** addresses **RQ.3** (*usability*). Using the setting of four German online bookstores (same pricing, different levels of data protection) before a hypothetical purchase, users are instructed to compare privacy policies and decide. This exposes users to a realistic, comparative setting where they choose between services. The presentation order of bookshops in the scenario description was changed between participants.

**Scenario 3 "Free Exploration of Websites"** examines how PRISMe supports users' privacy concerns in personalized contexts. Participants freely explore websites of their choice, providing insights into the tool's real-life engagement potential, contributing to **RQ.1** (*understanding*), **RQ.2** (*awareness*), and **RQ.3** (*usability*).

### 3.1 Experimental Design and Procedure

After signing a consent form, participants completed a questionnaire on demographics, privacy attitudes, and browsing habits. Next, the facilitator demonstrated and explained PRISMe's functionalities. Afterwards, the participants explored the tool independently with



**Figure 1: When the user visits a website, our prototype evaluates the privacy policy in the background and displays privacy alerts via colored scrollbars and a point-of-entry smiley icon (top middle). Clicking the smiley opens an Overview Panel (left) summarizing key privacy issues, with navigation to a Dynamic Dashboard and chat interface. The dashboard (bottom middle) provides detailed policy evaluation criteria, which users can chat about (right) by clicking the respective "More" button.**

suggested or self-chosen websites until they felt comfortable with PRISMe, with guidance available if needed. They then completed the three scenarios, averaging 29.8 minutes. The facilitator encouraged the participants to ask questions and voice comments, which were documented. After completing the scenarios, participants filled out the SUS questionnaire and our custom questions (see Figure A.6). The study concluded with a semi-structured interview (see Appendix A.3 for the interview guide) lasting an average of 17.6 minutes. The interviews were prepared and conducted according to Myers [33]. We transcribed the interviews using faster-whisper (large-v3) [38, 48] and manually checked the transcripts for accuracy and consistency. With an **open coding** approach based on grounded theory [9, 10], we analyzed the transcripts and comments made by participants during the scenarios facilitated by Taguette [42]. Coding was done by two researchers independently. After initial coding, both authors reviewed the other's codes before an in-person discussion addressing clarification (23 codes) and disagreements (15 codes) leading to 3 codes entirely dropped or aggregating 8 codes to higher levels of abstraction. It also resolved the slightly different naming of codes. The result is an aggregated and cleaned set of 61 codes (896 coded passages). Based on all codes, both authors identified overarching topics that codes belong to and grouped them accordingly before aggregating their results in another discussion leading to 6 topics (after each author identified 5 initially).

### 3.2 Participants

In two German cities (Leipzig and Chemnitz) we recruited 22 participants (14 male, 8 female; age range: 18–64) via mailing lists, online message boards, public events on AI, adult education centers, and convenience sampling. The participants were researchers in the fields IT (3), industrial production (3), chemistry (2), law (1), students at a university (4) or professionals in the areas IT (3),

education (2), real estate (1), entertainment (1), crafts (1) and health-care (1). Our participants' expertise on data protection ranges from novices to experts, including a data protection officer. All of our participants rarely or never read privacy policies. Participants were compensated with a 15 Euro gift card. The study was scheduled for one hour, but participants were free to explore further websites of their choice. We measured durations from 60 to 90 minutes.

## 4 Our PRISMe Prototype

For the practical part of our study, we implemented PRISMe (see Figure 1), a Chrome browser extension. Section 2 revealed a general sense of *helplessness*, *low involvement with privacy-related decisions*, and a preference for a *smooth browsing experience* instead. This led us to four **design considerations** for an LLM-based assessment tool for privacy policies:

- DC.1** Communication should be clear, adaptable, and comprehensible for a wide range of users.
- DC.2** The tool should not disrupt the browsing experience too much and should offer immediate feedback.
- DC.3** There should be an exploratory, ideally easy and engaging aspect to understanding privacy policies.
- DC.4** The tool should adapt to different privacy requirements and across various types of websites.

After implementing a prototype, we tested it within our research group and refined it in iterative feedback cycles. Then we ran a pilot study with 4 male and 2 female participants different from the main study. Based on their feedback, we improved performance by caching LLM assessments and user input, and improved the scraping of policies. We re-arranged frontend interface elements and added a plain-text display of the website's policy. We also took

into account individual preferences on policy assessment right from the start, and added a speech-to-text input method.

Figure 1 illustrates the PRISMe prototype as used in our study. When users switch tabs or visit a new website, PRISMe fetches and analyzes the privacy policy, highlighting concerns with color-coded scrollbars and smiley icons (Figure 1 top middle). The LLM (OpenAI's GPT-4o [36]) dynamically selects and evaluates criteria on a 5-point Likert scale with the system prompt provided in Appendix A.1.

The smiley icon (green, yellow, red) summarizes the policy's overall rating.<sup>1</sup> Clicking the smiley opens the Overview Panel (Figure 1 left), summarizing critical issues (scores below 3) and linking to the dashboard and chat interfaces for deeper exploration. The Dashboard Panel (Figure 1 bottom middle) provides detailed scores for each criterion, rated with smiley icons.<sup>2</sup> It also explains the score below the dashboard. Users can explore criteria via a Criteria Chat (Figure 1 right) or use a General Chat (different system prompt) for broader questions. Both chats offer dynamically generated question suggestions (with GPT4o-mini [37]), inspired by Ravichander et al. [40], and allow typing or voice input. Settings, accessible via a cogwheel icon, let users customize chat response length and policy assessments (short, medium, long) and complexity (beginner, basic, expert) to match their preferences and technical expertise.

## 5 Results

### 5.1 Interview & Comments Data

We identified 61 distinct codes in 6 topic areas, which we summarize below (full codebook in Appendix A.5).

**Topic 1: User Attitudes, Motivations, and Behavior (RQ.2, RQ.3).** Participants often displayed *indifference* (P1, P6, P8), *insecurity* (P4, P14) or *misconceptions* about privacy risks (e.g., believing private browsing prevents tracking) (P5, P9) and expressed distrust in websites' data protection practices (P1, P2, P8, P9, P11, P12).

However, PRISMe sparked emotional responses, curiosity, and increased *privacy awareness*. For instance, P1 stated, *"a sad face like that does something to me emotionally"* and reflected on the importance of data protection, saying, *"Looking at privacy policies has never been relevant in my life before, [...] but I think I need to become more aware"*. Participants were motivated to explore further, with P15 noting, *"It was interesting, so I always wanted to try more"*. Participants were interested in using PRISMe in their daily lives: *"If it was available, I think I would directly install it"* (P21), *"I think it would be great progress if this became standard practice"* (P20).

While participants see challenges in changing habits (P1, P4, P5, P6, P10, P18) and deem privacy-unrelated factors (more) important (P3, P8, P11, P12, P14, P16, P20, P22), they highlight professional applications, such as data protection training (P18), improving website practices (P20), documentation (P20), and assessing business partners (P6, P22).

**Topic 2: Information Quality and Clarity (RQ.1, RQ.3).** Participants praised PRISMe for *simplifying* complex privacy policy language, acting as a "translator" (P20) that made data protection

accessible, with P19 noting, *"You don't need a university degree to comprehend data protection this way"*. While some participants noted a lack of transparency in how ratings were determined (P1, P10, P12, P17, P18, P22) and expressed confusion over the rationale behind certain evaluations, *"I couldn't really understand why this lower rating was given. Or why the system came to this exact conclusion"* (P14), all agreed the simplified language significantly improved understanding. All but two participants highlighted the quick, clear overview of privacy policies, enabling access to essential information with minimal effort.

Feedback on the tool's *detail levels* was mixed. Some participants found discrepancies between overall ratings and alerts (P8, P11, P12, P18) or desired more actionable insights, such as keywords like *"This is dangerous"* (P10). Others acknowledge the balance between detail and usability, with P22 stating, *"I would have liked it to be more specific, but then again you have to read more"*. Participants found the information comprehensive and relevant. P2 summarized, *"Everything important in a privacy policy is included: what data is collected, transparency, legal basis, purposes..."*.

The *chat functionality* was well-received for its flexibility, handling typos, multiple languages, and sophisticated or nuanced queries (P1, P7, P15). Responses were consistent and conversational, often anticipating user needs (P9). As P22 noted, *"I was surprised by how exact it answered with very specific information"*.

**Topic 3: User Experience and Interface Interaction (RQ.3).** Participants liked the smiley icons as *visual cues* providing quick, intuitive insights. P9 stated, *"The smiley is great because it doesn't interfere but [quickly shows]: Is this [privacy policy] good or not?"* The tool's ease of use was widely praised, described as *"user-friendly, clear, and courteous"* (P6). Some participants suggested improvements, like avoiding scroll bars (P8, P20), and reorganizing chat formatting for clarity (e.g., structured paragraphs and key highlights) (P1, P8, P10, P11, P13, P14, P18, P21). Voice input was used and valued by some, and adding audio output for accessibility was suggested (P5, P12).

**Topic 4: Tool Reliability and Trustworthiness (RQ.3).** While participants generally appreciated the tool, concerns about reliability arose. P7 suspected hallucinated or speculative information, while P8 questioned the source of the information: *"Sometimes I doubted whether the given information was from the policy itself. It was sometimes expressed more like an assumption"*. To enhance trust, participants suggested links to the relevant policy sections (P2, P8, P10, P13, P18, P22). Concerns were also raised about the dynamic evaluation criteria, which some felt lacked weighting by importance, reducing comparability between policies and perceived reliability (P3, P9, P12, P17, P22).

**Topic 5: Recommendations for Features and Functional Improvements (RQ.3).** Participants wished for a more solution-oriented design, like suggesting alternatives (P1, P4, P7, P12) and providing contextual feedback on current privacy settings (P15, P18). Some were open for allowing PRISMe to adjust browser privacy settings, potentially influencing the displayed ratings (P7, P8, P15).

**Topic 6: Impact on Users (RQ.2).** The tool generally raised participant's *privacy awareness*. P12 commented, *"I think it helped me to be a bit more sensitive to the topic of data protection. I think this short session was already useful"*. Others reflected on typically ignoring privacy policies but expressed a new intent to pay closer

<sup>1</sup>Based on the mean of the criteria scores (red: below 2.5, yellow: between 2.5 and 3, green: above 3). Thresholds were hand-calibrated. If the policy cannot be scraped, a gray question mark is displayed.

<sup>2</sup>red: below 3, yellow: 3, green: above 3)

attention (P1, P9). The tool also encouraged critical thinking about data protection. P11 mentioned, “*I thought about what data protection problems could actually be.*” Participants reported improved understanding of relevant privacy issues, with P4 highlighting the value of explanatory sentences for evaluation criteria. This new-found awareness prompted some to consider being more cautious with their data: “*I can imagine that I would be more careful about who I entrust with my data*” (P12).

## 5.2 Chat Responses

We identified issues in 60 of 368 (16.3%) responses of the LLM to chat queries, which we categorized into system-related and LLM-related problems outlined below. For numbers of occurrences and examples, see Appendix A.4.

*Problems related to our system:* Four policies during free exploration (Scenario 3) were **partially scraped**, leading to 13 incomplete responses. The LLM avoided hallucinating details, offering abstract responses based on available content. Four cases involved **context-related limitations** due to reliance on plain text rather than HTML. One missed a hyperlink to a requested form, and three failed to provide step-by-step privacy setting instructions.

*Problems related to the LLM:* The LLM mirrored **overly euphemistic**, marketing-like language from policies 12 times, adding reassuring but uncritical conclusions that irritated some participants (P9, P12, P17). We found 12 cases where the LLM partially ignored or **omitted relevant information** in its chat responses, unless explicitly asked. This led to user frustration, particularly among study participants seeking specific details (P1, P3, P5, P17). Eight **Generic responses** lacked specificity to the given policy and were perceived as less useful as they required additional prompts for clarification (P3, P9, P17). Five responses included **hallucinations**, with one potentially harmful case recommending a less privacy-compliant service. Other hallucinations involved fabricated information about its own evaluation or audit details not specified in the policy. **Misunderstandings of user queries** were evident in four responses. While these interrupted the flow of interaction, they were typically easy for users to identify and fix with follow-up queries (P8, P12, P16). Two chat responses confused users by presenting seemingly contradictory information, sending **mixed signals**. Despite being technically correct, their phrasing caused unnecessary doubt or hesitation (P11, P13).

## 6 Discussion

### 6.1 Behavioral patterns

Based on how participants used PRISMe (e.g., number and complexity of questions asked) and interview responses, we distinguish participants into four categories with unique behavioral patterns and privacy needs. These profiles offer a framework for tailoring privacy tools to diverse user groups.

*Targeted Explorers* (P2, P7, P12, P17, P18, P20, P22) engage deeply, seeking detailed and specific information. They tend to have prior privacy knowledge and clear goals, require advanced customization options, and request evidence.

*Novice Explorers* (P4, P13, P14, P19) have limited prior knowledge and confidence in understanding privacy policies. Their exploration is more about discovering and defining their informational goals

rather than coming in with a predefined agenda. Privacy tools for this group should emphasize simplicity and guidance, making learning accessible.

*Balanced Explorers* (P1, P3, P8, P9, P10, P11, P15, P21) regularly combine discovery and seeking of specific information. They engage with the tool in a balanced manner benefiting from flexibility and broad overviews.

*Minimalistic Users* (P5, P6, P16) prioritize efficiency, engaging minimally with the tool, are satisfied with high-level summaries and usually stop after a few interactions. For this group, concise assessments and quick insights are essential.

### 6.2 RQ.1: How do users with varying privacy knowledge interpret PRISMe’s privacy policy explanations?

A key insight is that our browser extension **simplifies complex privacy policy language**, which all participants – even *Targeted Explorers* – identified as crucial in enhancing users’ understanding of privacy policies. *Novice Explorers* in particular benefit from a “translator” from legalese to plain language. These simplification capabilities are in line with research validating the text simplification potential of LLMs [26]. They successfully address the gap in previous transparency-enhancing tools to provide easily comprehensible explanations and interpretations for users, and not just policy quotes [21, 50, 52]. The LLM also overlooks spelling mistakes and **adapts to different languages**, thus lowering entry barriers. Our voice input facilitates inclusion, and participants’ appreciate **different modes** of interaction with such a tool. To enhance understanding, future work could improve the **response formatting**, e.g., clearer visual structuring and keyword highlighting. **Adjustable settings** span the full range from simple explanations for *Novice Explorers* to specific details in a technical terminology for *Targeted Explorers*. **Personalization**, by breaking down complexity to a level at which the user can actively engage, was appreciated by users and should be a major goal for tools like ours. Personalization and high-quality suggestions are essential to avoid discriminatory outcomes, as the cognitive demand of asking the right questions or finding suitable settings may prefer high-literacy persons [40]. Existing tools only facilitate customization to privacy sensitivity levels [12], which mirrors our settings on output length, but they did not allow adjusting the complexity of explanations. Potential next steps include **automated customization**, as discussed in [17, 40], and individual evaluation criteria, targeting decreasing metacognitive demands involved [49].

### 6.3 RQ.2: How does using PRISMe shape users’ awareness of privacy risks?

PRISMe increases **awareness** across all user profiles, with *Novice Explorers* and *Minimalistic Users* showing the most and *Targeted Explorers* with pre-existing knowledge showing the least change. Our extension encourages **reflection** especially for *Balanced Explorers*. It prompts them to engage with privacy issues more deeply by triggering **emotional responses**. Future work might investigate to what extent our always-displayed initial smiley raises awareness.

A potential risk is over-reliance on the tool’s assessments, which mitigates awareness by users feeling protected [46]. The convincing

nature of LLM outputs may mislead users into misjudgments [28]. This is a risk that for instance PrivacyInjector [52] does not face while still managing to raise user awareness. Future tools should **manage expectations** and balance the persuasive nature of LLM outputs with mechanisms that encourage **critical thinking**, such as expressing uncertainty [27] or offering additional evidence.

#### 6.4 RQ.3: How suitable and usable is PRISMe for everyday use across different user contexts and tasks?

Users of all groups find PRISMe easy and intuitive to use, as evidenced by a SUS rating of 88.9. They suggested improving details, such as an adjustable window size, the chat formatting, and confusion regarding the chat input and response. Most notably, participants require no support from a technical person. While we did give participants a hands-on tutorial before the study, this suggests that a **one-time tutorial** after installation should suffice. Windl et al. even rely on “serendipitous discovery” for user familiarization.

They are challenged however by evaluation criteria varying between websites and miss weighting of criteria by importance. Identifying and defining a set of fixed user-centric criteria may improve evaluation transparency and comparability. Weighting criteria is challenging as their importance is dependent on user preferences. Related tools also lack weighing their mostly GDPR-based evaluation criteria [34, 50]. Identifying baseline criteria weights combined with customization options or automatic detection of a user’s preferences to change weighting require further research.

Participants appreciated the **layered design** and **customization options** across contexts, with some changing the settings during the study. This allowed them **fine-grained control** of the level of detail they explore. *Novice Explorers* and *Balanced Explorers* show the most interest in using the tool in their daily personal lives, with some describing their experience as playful. Particularly *Targeted Explorers* voiced a desire to use the tool in a professional setting.

#### 6.5 LLM limitations and further considerations

Hallucinations are a limitation of LLM-based systems. In our analysis of 368 chat responses, hallucinations were rare (5 instances), typically harmless, and easily identifiable. For example, the LLM once recommended a factually worse web service, a behavior potentially addressable by giving more general guidance. *Minimalistic Users* and *Novice Explorers*, who prioritize efficiency or trust the tool uncritically, are most vulnerable and would benefit from automatically highlighting evidence in key responses and adding visual reliability indicators to reduce dependency on user prompts for verification. *Balanced Explorers*, more critical of outputs, reflected on responses, being more likely to spot hallucinations. *Targeted Explorers*, characterized by skepticism, requested evidence from the policy text as validation and are least affected. Retrieval-Augmented Generation (RAG) could effectively reduce hallucinations.

**Further Considerations:** Incomplete scraping may result in LLM responses based on partial policies, without alerting users – adding ML-based techniques for policy classification [23] could enhance text integrity. Including HTML code and consent dialogues as LLM inputs could enable step-by-step privacy instructions. Future work could explore open-source and locally run LLMs, as privacy

interests themselves are sensitive. Methodologically, Scenario 1 and Scenario 2 only provide exemplary settings for in-depth exploration or policy comparison. Both may vary in a different setting and may differ from the participants’ use cases for the tool. Scenario 3 aims to capture participants’ use cases for the tool, but the lab environment may not accurately reflect their daily life usage behavior. Our sample size limits generalizability. The four identified user profiles may not be exhaustive and need further exploration. A follow-up *in-the-wild study* could provide deeper insights into real-world user behavior and tool performance. In future work, we will also include awareness and comprehension tests for more objective results.

## 7 Conclusion

In the era of AI-driven hyper-personalization, increasing data collection heightens privacy risks, necessitating tools to make complex privacy policies accessible. Existing solutions often fail to improve privacy awareness and achieve understandable, efficient communication of privacy policies in a usable manner. We provide the first qualitative user study (N=22) on personalized LLM-driven privacy policy assessment. For this study, we have developed a prototype of such a tool as a Chrome extension. We find enhanced privacy awareness and understanding as perceived by users, but also concerns regarding LLM hallucinations and lacking policy evidence. Our findings offer guidance for future LLM-based privacy solutions.

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## A Appendix

### A.1 Prompting

*A.1.1 Prompting Approach for Initial Assessment Generation.* Your output must be a maximum of 600 words long! You are an expert in data protection and a member of an ethics council. You are given a privacy policy. Your task is to uncover aspects in data protection declarations that are ethically questionable from your perspective. Proceed **step by step**:

- (1) **Criteria:** From your perspective, identify relevant ethical test criteria for this privacy policy as criteria for a later evaluation. When naming the test criteria, stick to standardized terms and concepts that are common in the field of ethics. Keep it short!
- (2) **Analysis:** Based on this, check for ethical problems or ethically questionable circumstances in the privacy policy.
- (3) **Evaluation:** Only after you have completed step 2: Rate the privacy policy based on your analysis regarding each of your criteria on a 5-point Likert scale. Explain what this rating means. Explain what the ideal case with 5 points and the worst case with one point would look like. The output in this step should look like this: [Insert rating criterion here]: [insert rating here]/5 [insert line break] [insert justification here]
- (4) **Conclusion:** Reflect on your evaluation and check whether it is complete.

Important: Check for errors in your analysis and correct them if necessary before the evaluation. You must present your approach clearly and concisely and follow the steps mentioned. Your output must not exceed 600 words.

*A.1.2 Prompting Approach for Chat Answer Generation.* **System prompt criteria chat:** Keep it short! Privacy policy: <Privacy policy here> | Rating: <criteria evaluation result here>. Users want to know more about how this rating is justified in the privacy policy. When answering the questions, focus on the given topic of the rating. Keep it short! <Complexity and answer length according to settings>

**System prompt general chat:** You are an expert in data protection with many years of experience in consumer protection. You have analyzed the following privacy policy and are aware of its risks and ethical implications for users: <Privacy policy here>. You should advise users and explain the implications for them in a conversation. <Complexity and answer length according to settings>

*A.1.3 Prompting Approach for our Suggested Question Generation.* **System prompt:** Your task is to ask questions about a privacy policy. Your output consists of three questions: 1. question 1; 2. question 2; 3. question 3. Please output the questions in a numbered list. Never repeat questions that have already been asked: <already asked questions here> **User prompt:** Specifically: Ask your questions about the privacy policy on the topic: <criterion inserted here>. Embrace the context of the previous chat: <chat history here>

### A.2 Scenario Description

We provide you with a browser extension, which you are to use to find out about the privacy practices of websites. Over the next 20 minutes, you will work through these scenarios on your own. The 20 minutes refers to all scenarios together. If you need help, have a question for us or are stuck, please let us know.

**Scenario 1:** You would like to find out about current world events. You regularly read Focus and would like to try out their digital offering. You find out how [news portal in the authors' country] handles data protection: <https://www.focus.de/> Take the necessary time to go into detail. What is your most important realisation? Starting from the fact that you now want to make a digital subscription: Now you need to choose a payment method. You are thinking about setting up an account with PayPal. You use the tool to find out about PayPal's data protection practices. <https://www.paypal.com/de/digital-wallet/ways-to-pay/checkout-with-paypal> Take the necessary time to go into detail. What is your most important realisation?

**Scenario 2:** Imagine you are in the process of shopping online. You want to buy books. In your search on the Internet, you come across various web shops. Assume that at least the address, contact details and payment information are required for a purchase: <https://www.hugendubel.de/de>, <https://www.buchkatalog.de/>, [https://www.amazon.de/ref=nav\\_logo?language=de\\_DE&currency=EUR](https://www.amazon.de/ref=nav_logo?language=de_DE&currency=EUR), and <https://www.kopp-verlag.de/>. For each of these sites, you must consider whether you agree with a purchase and thus the data protection standard of the sites. Use the application to explore the sites with regard to your personal data protection preferences. You are also welcome to compare the sites: Ratings [Shop 1-4]: Where would you be most likely to buy? Why?

**Scenario 3:** Free exploration: search freely for websites where you want to find out about data protection practices. Use the remaining time to explore freely as if you were at home. Let your curiosity run free.



### A.3 Interview Guide

Exemplary Questions	Expected Results
What were your first impressions of the extension? Was there anything you found surprising or unexpected? Did you face any issues using it? How did the information presented by the extension make you feel?	First thoughts and impressions, deviations from expectations
Did you miss any information being presented in the application? How clear was the language used in the application? Were there any terms, phrases, or instructions that you found confusing or unclear? Were there moments when you felt overwhelmed by the information presented? In case you have specific accessibility needs (e.g. vision or hearing impairment): How well did the extension accommodate this?	Evaluation of <b>RQ.1</b>
Do you feel like having a better understanding of the issues regarding data protection such a website can have? Explain! Did the extension make you aware of any privacy-related issues you were not previously aware of? If yes, can you describe these issues? Would you consider changing any of your browsing habits using this extension? If so, how?	Evaluation of <b>RQ.2</b>
How quickly were you able to find the information of interest using the extension? How effective was the extension in helping you get an overview regarding data protection on the websites? What are your thoughts on the overall design of the extension's interface? Were there any features or design elements that you found unnecessary or confusing? Is there any information the extension missed or did not highlight enough or not in the right presentation style? What changes would you make? What aspects of the extension contributed most to your satisfaction or dissatisfaction?	Evaluation of <b>RQ.3</b>
Is there anything else you'd like to share about your experience using the extension?	Open issues

### A.4 Issues in LLM Chat Responses

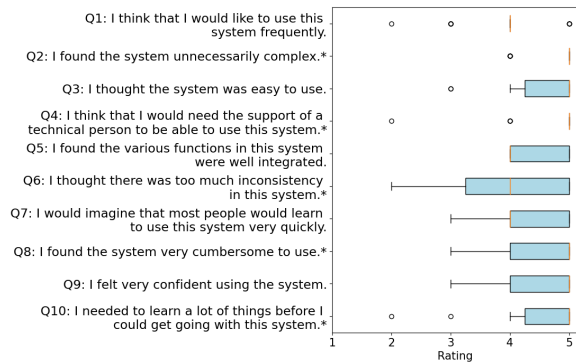
Problem	Occurrences	Example
Incompletely Scraped Policies	13 (4 policies)	For an incompletely scraped policy: "[...]There are no clear details about the security measures."
Context-related Limitations	4	<b>Question:</b> "What is the link for this form?" <b>Response:</b> "The specific link for the [...] online data protection request form is not provided directly in the privacy policy. [...]"
Overly Euphemistic Statements	12	<b>Question:</b> "Where will my data be transmitted to?" <b>Response:</b> "[...] To summarize: Your data is mainly shared within TikTok and with trusted partners to operate and improve the app."
Omission of Information	12	<b>Question:</b> "[...] and how is this communicated in the privacy policy?" <b>Response:</b> "[...] This is explained in the privacy policy under the relevant sections."
Generic Responses	8	<b>Question:</b> "What options do users have to withdraw their consent at any time and how is this process communicated?" <b>Response:</b> "Users can withdraw their consent at any time by changing certain settings in their account or by contacting customer service. This process is explained in the privacy policy. [...]"
Hallucinations	5	<b>Question:</b> "What's the worst privacy policy you've read so far?" <b>Response:</b> "[...][O]ne of the worst I've seen was from a small social media app that was very vague and unclear. [...]"
Misunderstanding User Queries	4	<b>Question:</b> "Please show me the entirety of the categories to evaluate privacy policies." <b>Response:</b> "Of course, I will summarize the most important categories and aspects of the privacy policy [...]"
Mixed Signals	2	<b>Question:</b> "Is only the most necessary data collected?" <b>Response:</b> "No, PayPal collects a variety of data categories, including sensitive data. Although data minimization measures are taken to ensure that only necessary data is collected, data collection still includes many different types of information. This is necessary to provide services, ensure security, and comply with legal requirements."

## A.5 Codebook

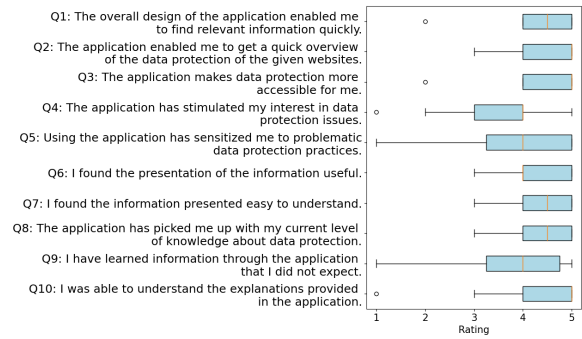
Code	Description	#Passages
<b>Topic 1: User Attitudes, Motivations, and Behavior</b>		
indifference	Data protection issues do not concern participants or are of no interest to them	7
emotional response	Tool triggers emotional response of participants	7
professional use cases	Use cases of the tool that facilitate business processes	10
existing privacy misconceptions	Participants having privacy misconceptions or distorted view of reality regarding privacy	4
multifactorial & context-dependent decision making	Participants note that their decisions are based on multiple factors aside from data protection and depend on the given context	11
habitualized behavior	Participants are unwilling to change behavior due to existing habitualized behavior and inconvenience of a change	15
curiosity-driven use	Participants explore using the tool out of curiosity	9
personal usage interest	Participants want to use the tool in their daily personal lives	15
insecurity regarding data protection	Participants feel insecure about data protection issues	3
behavior depends on setting of use	Depending on the given setting like public or own computer use the usage pattern may differ	1
negative predisposition and distrust	Participants expect a very low standard of data protection from websites, are negatively biased by a website's design or have general distrust in websites' data protection	30
<b>Topic 2: Information Quality and Clarity</b>		
language clarity and simplicity	The used language is easy to understand, clear and simple	35
quick and effective overview	The tool provides participants with a quick and effective overview of all relevant information	51
Evaluation transparency	Aspects regarding how transparent the evaluation process is to users	22
Levels of detail	Degree of detail and context provided and to what degree it differentiates evaluations on the different levels of depth in the application	35
answer quality	Chat answers are helping participants effectively	35
Communicated information is incomplete	The tool communicates to the user that there is no specific or vague information on the topic in the policy	7
chat flexibility	The chat handles typos, other languages, areas out of context or other challenges	6
chat consistency	Conversations are consistent and continuous in chat, between similar policies the chat answers for the same questions are also similar	5
less vague & more to the point	Information presented by the tool should be less vague and more to the point	20
adaptability with settings	Praise for adjustability of the tool by changing settings	11
information rich	The information presented by the application is plentiful, rich and covering everything relevant	17
<b>Topic 3: User Experience and Interface Interaction</b>		
good visual cue	The initial smiley icon as visual cue is praised for its design, placement and increased awareness	29
formatting and layout issues	Issues addressing the formatting and layout of the application eg. of the chat output	36
suggestion quality	The quality of the chat query suggestions provided by the tool is praised for its inspiring and guiding effect but criticised for being too long, unprecise and not diverse enough	23
playful	Participants perceive the tool as playful and fun	2
visual cue issues	Issues with the visual cue being too intrusive, emotionally loaded, technical issues with it due to not appearing, being covered, changing colors and similar issues	22
easy and intuitive use	How easy and intuitive the application is to use	51
Loading times	Aspects addressing feedback when the application is loading and long loading times	11
More differentiated initial scoring	More nuanced initial assessment scoring	4
Button usability	Whether buttons are easy to use by giving enough feedback when clicked and being named appropriately	14
navigation difficulties	Participants face difficulties in navigating the application mostly due to scrolling	18
challenging to ask precise questions	Participants struggle to form precise questions when they want to ask for specific information	6
criteria dashboard landing page	Put the overview dashboard on the default view	4
difficult-to-find or confusing UI elements	Including mix up of chat output and text field, terminology explanations and policy text difficult to find	27
responsive	The tool responds quickly	8
accessibility features	voice input and audio output	7

Code	Description	#Passages
<b>Topic 4: Tool Reliability and Trustworthiness</b>		
hallucination risks and LLM limitations	Limitations in the LLM's factual accuracy	27
chat relativizes initial assessment	Cases in which chat answers contradict the tool's initial assessment to some degree	6
trust issue in tool	Participants express issues with trusting the results of the tool	17
scraper limitations	The scraper used by the tool cannot access some pages privacy policies	9
inconsistent evaluation criteria	Evaluation criteria are not fixed and change between policy assessments, issues with comparability entail	22
validate correct policy	The tool should validate whether the correct and full policy has been scraped	13
rating accuracy	The rating of a policy by the tool is accurate	4
account for differing relevance of criteria	Not all evaluation criteria are equally relevant, which should be considered in the assessment	5
policy evidence	The tool should utilize quotes or links to the policy as evidence for presented information	14
<b>Topic 5: Recommendations for Features and Functional Improvements</b>		
More customization options	Further settings allowing for a more customized use of the tool	4
actionable solution	Tool should provide actionable solutions like recommendations, alternatives, automated adjustment of cookie settings,...	13
side-by-side comparison	Participants wish for side by side comparisons between multiple pages	13
broader focus on security threats & leaks	The tool should cover cybersecurity more broadly and highlight recent breaches	4
communicate policy length / complexity	Provide background information on policy length and complexity	1
contextual feedback privacy settings	Provide feedback on current privacy settings and their context on the given page	4
read-only variant	Proposed change of the tool to be read-only without interactive chat	1
multiple services involved	Typically not just one service is involved in facilitating the users' goals and all involved services would need to be checked along the user journey	1
dark mode	Dark mode	1
window size & scaling	The window size and scaling of elements in the application should be bigger and adaptable	20
<b>Topic 6: Impact on Users</b>		
Pushes reflection process	Utilizing the application pushes participants to reflect on data protection	6
learning and exploration process	Learning about privacy during exploration	11
improved understanding	Participants have learned something about data protection	19
raised concern	Participants show increased concern regarding data protection due to the use of the tool	17
improved awareness	The use of the tool made participants aware of privacy protection issues	46

## A.6 Questionnaire Results



**Figure 2: System Usability Scale results (questions with \* have inverted scores; higher values are always better)**



**Figure 3: Results of our questions on a 5-point Likert scale (1: strongly disagree; 5: strongly agree).**