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Article

Exploring the cognitive and emotional impact of deceptive patterns: an EEG, eye-tracking, and sentiment analysis of user experience

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Abstract

This study investigates the cognitive and emotional impacts of specific "Deceptive Patterns" in user interface design on well-known online platforms: Facebook, Instagram, Spotify, Salesforce, Eventbrite, and PayPal. The focus is on two types of deceptive patterns, "hard to cancel" and "hidden subscription" practices. Employing an integrated methodology of electroencephalogram (EEG), eye-tracking, and sentiment analysis, this research analyzes how these patterns influence user behaviour, attention, and emotional responses. The study utilized EEG to measure cognitive load as users interacted with "hard to cancel" interfaces revealing that these platforms increase cognitive demands, inducing greater mental effort and frustration. Eye-tracking data demonstrated that platforms with more transparent mechanisms effectively captured and held user attention on the Terms and Conditions as the key elements, thereby fostering user trust and enhancing transparency. Sentiment analysis further assessed users' emotional responses, underscoring the positive association between transparent interfaces and user satisfaction. This research highlights the importance of ethical design practices that prioritize user autonomy and transparency, offering a unique methodological contribution through the combined use of EEG, eye-tracking, and sentiment analysis to comprehensively capture cognitive and emotional responses.

RESEARCH HIGHLIGHTS

- This study examines how deceptive patterns on online platforms, such as "hard to cancel" and "hidden subscription," affect users' cognitive load, visual attention, and emotional responses.
- Using EEG, eyetracking, and NLP-based sentiment analysis, it provides a detailed picture of how these deceptive patterns increase mental effort, obscure decisionmaking, and undermine user trust.
- The findings underscore the importance of transparent, ethical design practices that protect user autonomy and satisfaction.

Keywords: *deceptive patterns; EEG; eye tracking; cognitive load; user experience*

1 Introduction

Deceptive Patterns (DPs) are intentionally designed user interfaces that deliberately mislead or confuse users, hinder them from clearly expressing their true preferences, or manipulate them into making specific choices. These patterns often leverage cognitive biases to influence online consumers, encouraging them to buy unwanted products or services or disclose personal information they would rather keep private. These patterns are deceptive design tactics that trick or coerce users into actions they might not otherwise take, often benefiting the platform at the user's expense (Luck & Gaspelin, 2017). It is important to note that while the term "deceptive patterns" is widely used in both academic and regulatory contexts, not all such patterns are strictly deceptive in the legal or psychological sense. Recent scholarship highlights that many interface practices commonly grouped under this label may be more accurately described as obstructive, introducing friction or barriers to user action, or sneaky, by avoiding user detection or clear disclosure, rather than overtly deceiving users. For example, "hard to cancel" patterns are primarily obstructive or coercive, making it difficult for users to complete desired actions, while "hidden subscription" tactics often operate by concealing information or using subtle cues rather than direct deception. Throughout this paper, we use the term "deceptive patterns" for consistency with established literature, but we also distinguish between deceptive, obstructive, and sneaky tactics where appropriate, and note where alternative terminology such as "manipulative" or "obstructive" patterns may be more precise. This nuanced approach aligns with recent theoretical frameworks and ensures that our analysis accurately reflects the diversity of manipulative strategies found in contemporary interface design. Patterns can quietly push users into choices that help the platform but may not be in the user's

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best interest, often without them fully realizing it. In 2010, when Brignull first coined the term "Deceptive patterns" on the website,[1] he defined these user interface designs as "tricks used in websites and apps that lead you to do things you didn't intend to, such as making a purchase or signing up for something." Brignull's pioneering work sparked a wave of academic research focused on defining and describing patterns. These patterns can also include unintentionally subscribing to services or encountering difficulties when trying to cancel subscriptions (Mathur *et al.*, 2019). Previous researchers have found, the "Hidden Subscription" pattern is where users are unknowingly enrolled in a recurring subscription or payment plan without clear disclosure or their explicit consent, and "Hard to Cancel" pattern is where users find it easy to sign up or subscribe but difficult to cancel (Mathur *et al.*, 2019). Luguri and Strahilevitz (Luck & Gaspelin, 2017) have identified hidden subscriptions as one of the most effective Deceptive Pattern strategies, while Ibarra (2017) has highlighted the potential manipulative intent behind making account cancellations intentionally difficult. Based on these insights, "Hidden Subscription" and "Hard to Cancel" patterns were selected as the focus of this study, given their significant impact on user autonomy and experience.

2 Rationale for Research Questions and Hypotheses

The research questions were formulated based on an identified gap in the existing literature. While many studies on deceptive patterns (DPs) focus on legal, ethical, or interface design perspectives, few empirically investigate their cognitive and emotional impacts using physiological measures. To address this gap, we developed three interlinked research questions: (RQ1) focuses on cognitive load, (RQ2) explores visual attention, and (RQ3) considers the integration of emotional and cognitive responses. These were intentionally selected to reflect a holistic approach, aligned with our triangulated methodology using EEG, eye-tracking, and sentiment analysis. Our early pilot tests and interface reviews also revealed that certain deceptive patterns including buried interface elements, substantially influence user attention and decision-making more than anticipated. These observations informed the direction of our cognitive and visual hypotheses.

3 Research Questions

1. How do deceptive patterns affect users' cognitive load during account deletion processes? 2. How do deceptive patterns affect user visual attention during sign-up processes? 3. How can EEG, eye-tracking, and sentiment analysis be integrated to provide a holistic understanding of users' interactions with deceptive patterns?

4 Hypotheses

1. Users will experience a higher cognitive load when interacting with websites that employ "Hard to Cancel" patterns compared to those that are easier to cancel. 2. Eye tracking data will show that users exhibit shorter fixation durations and longer Times to First Fixation on the Terms and Conditions or Privacy Policy section on websites with Hidden Subscription DPs employing implicit consent. 3. Cognitive load, visual attention, and emotional responses interact dynamically when users encounter deceptive patterns, with changes in one factor influencing the others. These interactions can be observed through EEG, eye-tracking, and sentiment analysis, providing insights into how deceptive patterns impact user behaviour and experience.

5 Literature Review

The study of DPs in user interface design, particularly associated with privacy, has seen significant expansion in recent years. These patterns are essentially deceptive design elements that manipulate users into taking actions they might not have intended, such as purchasing products or signing up for services (Brignull, 2019). One critical aspect of DPs involves the specific characteristics of user interfaces that influence user behaviour. In our previous study, we examined the impact of "Hard to cancel" and "Hidden subscription" deceptive patterns using a mixed-methods approach, combining eye-tracking, facial electromyography (EMG), and sentiment analysis to assess user attention, emotional response, and perception. The findings showed that obfuscated cancellation processes and implicit consent mechanisms not only resulted in stronger negative emotional reactions, but also reduced user noticeability of important terms. These results highlight the significance of transparent design and regulatory intervention to mitigate the adverse effects of deceptive UX patterns (Jamalifard *et al.*, 2024). Various definitions have emerged to describe these characteristics, often using terms such as "tricks" or "misleading" (Brignull, 2019, Waldman, 2020). Mathur (Mathur *et al.*, 2019) contribute to this discussion by characterizing DPs as designs that "coerce, steer, or deceive," while Gray *et al.* (2024) emphasize the "obnoxious, coercive, or deceitful" nature of these interfaces. The role of the designer is another focal point in the literature. Some researchers argue that designers exploit their knowledge of human behaviour to create these patterns intentionally. This concept is rooted in earlier discussions, such as Fogg (1998) exploration of how "persuasive technologies" can be used to deliberately influence users. These discussions highlight the ethical considerations designers must navigate when balancing the effectiveness of their designs with potential manipulative consequences. Given the power designers hold in shaping user behaviour, the primary approach for conveying information about privacy protections to end-users has been through notice (awareness) and consent (choice) mechanisms. This model typically involves the use of privacy policies and opt-in/out interfaces, which are legally recognized as "pre-formulated declarations of consent" or "clickwrap" agreements. However, the effectiveness of these mechanisms is often compromised, as privacy policy notices are particularly problematic, requiring significant time to read and a high level of reading comprehension. As a result, users rarely engage with these policies before accessing a site or service, often consenting without reviewing or even noticing them (Brignull, 2019). Therefore, it becomes clear that implementing an ethical design is essential to ensure that users notice and fully understand the terms and conditions before signing up for a platform. By prioritizing ethical design practices, designers can help bridge the gap between user awareness and consent, making it easier for users to engage with and comprehend the information provided, thereby fostering informed decision-making and protecting user rights (Negi & Mitra, 2020). Furthermore, DPs are also examined concerning the outcomes they produce both beneficial and harmful. Some definitions suggest that these patterns are crafted to benefit the online service providers, often at the

[1] https://www.deceptive.design/

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expense of users. This is particularly evident in examples such as the "Hidden Subscription" and "Hard to Cancel" patterns. These patterns mislead users about recurring fees or make it unduly difficult to cancel subscriptions, thereby restricting user choices and obscuring essential information (Maier & Harr, 2019). For instance, Brignull (2023) describes the "Hard to Cancel" pattern, also known as the "Roach Motel," where signing up for a service is easy, but cancelling it is deliberately made complicated, often requiring users to navigate through customer service hurdles or prolonged processes. In addition to the research on DPs, significant attention has been paid to the role of social networking sites (SNSs) like Facebook in shaping online identity. SNSs provide users with the tools to create public or semi-public profiles, connect with others, and monitor these connections. Facebook, with over 500 million registered users as of 2011, is a leading example, significantly outpacing competitors like Myspace, LinkedIn, and Twitter (Russell-Rose & Makri, 2012). Just as SNSs have reshaped online identity, the emergence of streaming services has similarly transformed the music industry, with platforms like Spotify revolutionizing access to music. Spotify has maintained its leadership position despite fierce competition by continuously evolving its business model, appealing particularly to younger users aged 18–35 (Gomes *et al.*, 2021). The discussion of user interaction with digital platforms also brings cognitive load theory into focus, particularly in relation to interface design. Cognitive load theory, initially proposed by Sweller (1988), posits that instructional design should avoid overloading the learner's working memory to maintain effectiveness (Steinfeld, 2016). Complex or challenging interfaces can increase cognitive load, thereby diminishing the learning process' efficiency. Cognitive load can be mitigated by using epistemic actions—physical actions that simplify mental processes (Kirsh & Maglio, 1994). To further understand the cognitive processes involved in interacting with these interfaces, electroencephalography (EEG) has emerged as a valuable tool in educational psychology for measuring cognitive load. EEG can track subtle fluctuations in cognitive load, providing insights into how instructional interventions impact cognitive processing. Research has indicated that specific brain wave rhythms, particularly alpha and theta waves, are sensitive to task difficulty and cognitive performance. These waves suggest that the brain exerts more effort to process information and focus on relevant tasks while filtering out distractions (Antonenko *et al.*, 2010). Moreover, eye-tracking technology has become increasingly important in evaluating usability and user experience (UX). Eye tracking allows researchers to analyse how users interact with a product, identifying usability issues and leveraging machine learning to recognize emotional responses linked to these interactions (Nouwens *et al.*, 2020). In summary, the expanding body of literature on DPs, social networking, streaming services, cognitive load, and EEG highlights the complexities of user interface design and its impact on user behaviour and cognition. These studies underscore the need for ethical design practices that prioritize user autonomy and transparency, ensuring that interfaces serve users' best interests rather than manipulating them for commercial gain. Retrospective Think Aloud (RTA) sessions are typically part of eye-tracking studies (Laan *et al.*, 2015), and sentiment analysis is a common approach to analyse the data from these sessions, Sentiment analysis and opinion mining are fields of study that analyse people's opinions, sentiments, evaluations, attitudes, and emotions from written language. It is one of the most active research areas in natural language processing and is also widely studied in data mining, web mining, and text mining (Leiser & Santos, 2023). To strengthen the theoretical framing, we explicitly situate "hard to cancel" and "hidden subscription" within the three-level ontology of dark patterns introduced by Gray *et al.* (2025). At the high level, "hard to cancel" exemplifies the strategy of Obstruction, where user autonomy is undermined by introducing friction or barriers to cancellation, while "hidden subscription" aligns with Sneaking, in which recurring charges or terms and conditions are deliberately obscured. At the "meso level", these patterns manifest as Roach Motel (easy entry, difficult exit) and Sneak into Basket or Hiding Information (e.g., pre-selected options, no checkbox/implicit consent mechanisms, unclear disclosures), respectively. At the low level, they are operationalized through specific interface elements, such as multi-step cancellation flows, hidden or ambiguously labeled options, fine print, pre-checked boxes, or the absence of explicit consent mechanisms. This mapping clarifies our rationale for selecting these patterns, demonstrates their alignment with established taxonomies, and illustrates how they manifest at different points in the user journey, from onboarding and sign-up (hidden subscription) to cancellation (hard to cancel) (Sandkühler & Bhattacharya, 2008). While prior research has extensively explored user awareness, felt manipulation, and self-reported frustration in response to deceptive patterns (Bongard-Blanchy *et al.*, 2021, Gray *et al.*, 2021a, Luguri & Strahilevitz, 2021), these studies have predominantly relied on surveys, interviews, or behavioral metrics such as task completion time. Our study builds on this foundational work by integrating EEG and eye-tracking to capture cognitive load and visual attention in real time, offering objective physiological data that can reveal subtle or unconscious effects of manipulative interface elements. As EEG allows us to detect increased mental effort and frustration during interactions with "hard to cancel" flows, while eye-tracking highlights how hidden or ambiguous elements affect users' visual search and comprehension. This approach enables a more granular understanding of how specific dark pattern features impact user experience, complementing and extending the self-report and behavioral findings of earlier studies.

6 Methodology

The website selection was based on (1) global popularity, (2) prior documentation of deceptive patterns in academic and regulatory sources, and (3) symmetry across the user journey, with sites representing both entry and exit flows. The "easy" vs. "hard" classification was informed by a pilot review and published audits (Sandkühler & Bhattacharya, 2008).

To investigate the impact of "Hidden Subscription" and "Hard to Cancel" patterns on user behavior, this study employed a mixed-methods approach (Figure 1). The study utilised real platforms to ensure that participants' behaviours were natural and reflective of real-world online interactions. This approach was chosen to simulate actual navigation behaviours and interactions, providing valid results. For "hard to cancel" task, EEG was utilized to measure the cognitive load experienced by participants as they attempted to cancel accounts on various websites, and for the "hidden subscription" task, eye-tracking was employed to observe how participants interacted with websites using either implicit or explicit consent mechanisms for subscriptions. To complement the quantitative data from EEG and eye-tracking, a Retrospective Think Aloud session (Perrin *et al.*, 1989) was conducted after participants completed the tasks. This session allowed participants to verbalize their thought processes while reviewing recordings of their interactions, providing deeper insights into their cognitive and emotional responses to the patterns.

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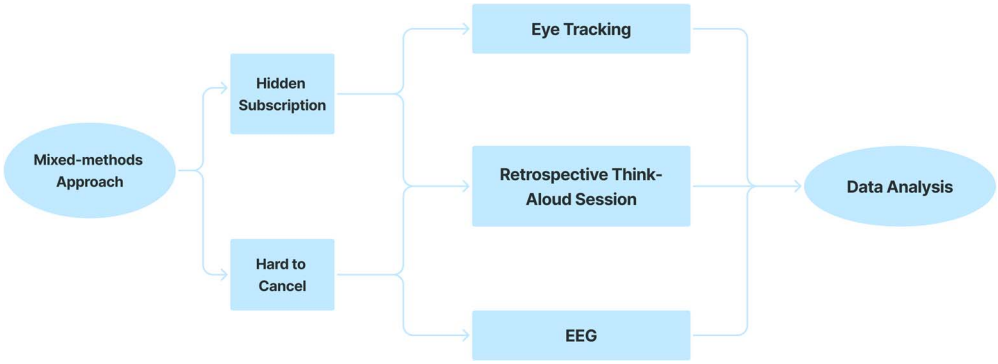

FIGURE 1. Mixed-methods approach methodology.

6.1 Variables

The independent variables in this study were the type of DPs (hard to cancel vs. hidden subscription) and the type of consent mechanism (implicit vs. explicit) used on the websites. The dependent variables included cognitive load, measured through EEG data, and visual attention, measured through eye-tracking data. EEG data focused on alpha and theta signals to measure cognitive load (Klimesch, 1999), while eye-tracking metrics focused on Time to First Fixation and Average Fixation Duration (Sweller, 1988).

7 Participants and data collection

The study included 30 participants, all of them were master's students from Goldsmiths, University of London. For the EEG study, 10 participants (six female and four male) were recruited, with ages ranging from 18 to 40. Similarly, the eye-tracking study involved 20 participants (twelve female and eight male) within the same age range. Participants were informed about the general nature of the experiment, though the specific goal was not disclosed to avoid introducing bias into their responses and behaviour during the experiment. The location of the experiment was the UX lab located in Goldsmiths, University of London. The ANT Neuro eego sports amplifier was used to measure brain activity with a sampling frequency of 500 Hz. Tobii Pro Lab screen-based eye-tracking software was employed to collect data on eye movements, with a sampling frequency of 60 Hz and a 10 ms interval. All participants first completed a pretest questionnaire to gather demographic data. The study then involved two groups: 10 participants completed account deletion tasks and 20 participants engaged in sign-up tasks. The websites were presented in a randomized order to minimize potential learning effects and eliminate biases and all accounts used in the study were fictitious to protect participants' privacy. All experimental sessions were conducted in the UX Lab at Goldsmiths, University of London, using the same desktop computer setup for every participant to ensure consistency. Each participant used a 24-inch Full HD monitor (1920x1080 resolution) connected to a Windows desktop PC equipped with an Intel Core i7 processor and 16GB RAM. The EEG and eye-tracking software (ANT Neuro and Tobii Pro Lab, respectively) were pre-installed. No mobile or tablet devices were used. This desktop-based setup was intentionally selected to control for display size and interaction differences, although we acknowledge that mobile interfaces may offer distinct user experiences. The participant sample in this study selected primarily for convenience. While this group likely possesses above average digital literacy, it may not be representative of the broader population in terms of platform familiarity or prior experience with subscription cancellation. All experimental tasks were conducted using newly created, fictitious accounts to protect participant privacy and ensure a standardized experience. As a result, participants did not face real-world stakes such as loss of data or disruption of established workflows, which can influence engagement and emotional responses during actual account cancellation (Gray *et al.*, 2021b, Sandkühler & Bhattacharya, 2008). The cancellation and sign-up flows used in our tasks were closely modeled on empirically documented dark pattern practices, including multi-step processes, hidden options, and implicit consent mechanisms, to ensure ecological validity. However, we acknowledge that the absence of personal investment and the use of a convenience sample may limit the generalizability of our findings. Future research should consider more diverse participant pools and real-world account scenarios to better capture the full range of user responses to dark patterns.

8 Task 1: Hard to Cancel

Participants were asked to delete accounts on six different websites, categorized as either hard or easy to cancel by the researchers. The websites included Spotify, Instagram, and Facebook (hard to cancel), as well as Quora, Pinterest, and LinkedIn (easy to cancel which representing the control condition).

9 Task 2: Hidden Subscription

Participants were asked to sign up for services on six different websites, interacting with both implicit consent mechanisms (Instagram, Facebook, LinkedIn) and explicit consent mechanisms (Eventbrite, PayPal, Salesforce, which representing the control condition). After completing the tasks, participants were debriefed, and their data was securely stored for analysis.

10 RTA Sessions for Both Tasks

After completing the tasks in both the EEG and eye-tracking studies, participants attended RTA session while watching a video recording of their screen interactions. This method was used to gather detailed insights into their experiences, to better understand their thought processes during the tasks, and to explore their prior experiences with these platforms and similar tasks. The interviews were recorded with consent, transcribed, and subsequently used in the study (Guan *et al.*, 2006).

11 Ethical Protocols

Ethical considerations were thoroughly addressed to ensure the protection and well-being of the participants. Informed consent

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was obtained from all participants before the start of the study. To protect participants' privacy, fictitious accounts were used during both the EEG and eye-tracking studies, ensuring that no personal data was collected or compromised. The study procedures were designed to minimize any potential discomfort, and participants were free to withdraw at any time. After completing the tasks, participants were debriefed on the purpose of the study and their role in it. All collected data, including EEG recordings, eye-tracking data, and interview transcripts, were securely stored on the OneDrive service provided by Goldsmiths, and were deleted from the recording devices and local storage immediately after the study.

11.1 Participant Experience and Ecological Considerations

It is important to note that all participants in this study used newly created, fictitious accounts and were not required to have prior experience with the platforms under investigation. While this approach ensured a standardized experimental setup and protected participant privacy, it may have influenced the extent to which users noticed or reacted to obstructive elements within the interface. Recent work by Gray *et al.* (2021b) highlights that the effectiveness of dark pattern tactics, such as those discouraging cancellation, can be moderated by a user's familiarity with the platform or their vested interest, such as sunk costs or the potential loss of data. In our study, the absence of real-world stakes may have reduced the emotional salience and stress typically associated with account cancellation or subscription management. We acknowledge this as a practical limitation and recommend that future research systematically examine how prior experience, account tenure, and personal investment moderate user responses to dark patterns.

12 EEG Data Preprocessing

The raw EEG data is loaded from the specified file using MNE (a software package for processing and analysing neurophysiological data), library to read the data into memory. The data was resampled to 250 Hz using the resample method (MNE 1.8.0 Documentation, 2024). This sampling frequency of 250 Hz was chosen to retain essential EEG information while reducing data size. A high pass filter at 0.10 Hz was applied to remove slow drifts, and a lowpass filter at 125.00 Hz was used to eliminate high-frequency noise, ensuring the data was within a range suitable for EEG analysis (Ifeachor & Jervis, 2002). After filtering, the data analysis focused on extracting specific EEG oscillations, namely alpha and theta waves, which are related to cognitive load, and removing artifacts from the data. After the initial preprocessing, the channels were mapped to the standard 10–20 montage to ensure consistency and accuracy in the analysis. The alpha channels (P3, P4, O1, O2) were selected because alpha waves are primarily observed in the posterior regions of the brain, which are linked to relaxation and reduced cognitive load. The configurations P3–O1 and P4–O2 refer to the specific bipolar electrode placements used in EEG data recordings (Bazanova & Vernon, 2014). Theta channels (Fp1, Fp2, F7, F3, Fz, F4) were chosen as theta waves are typically recorded in the frontal regions and are related to cognitive processing and load. Alpha waves characterized by frequencies ranging from 8–12 Hz, and Theta waves range from 4–7 Hz (Klimesch, 1999). In these configurations, the P3 and P4 electrodes are referenced against the O1 and O2 electrodes, respectively, to measure the difference in electrical potential between these points. This bipolar setup is often used to focus on specific brain regions, enhancing the ability to detect localised neural activity (Del Percio *et al.*, 2023). In the next step, referencing the EEG electrodes to an electrode in the contralateral hemisphere was a critical part of preprocessing the EEG data. Each electrode was referenced to one in the opposite hemisphere, emphasizing the differences in voltage due to actual brain activity while reducing common electrical noise (Yao, 2001). Interpolating bad channels was conducted to handle data from electrodes that might have malfunctioned or recorded poor-quality signals during the EEG session. By identifying these channels and replacing their data with interpolated values derived from surrounding channels, the continuity and quality of the EEG data were preserved. Interpolation ensured that the final dataset was more uniform and reliable (Ouzts & Duchowski, 2012). The specific channels selected for this study included Fp1, Fp2, F7, F8, F3, F4, P3, P4, O1, and O2. These electrodes are strategically positioned to capture signals from the frontal, central, parietal, and occipital regions of the brain, which are essential for studying cognitive load (Antonenko *et al.*, 2010).

12.1 EEG Data Analysis

After the previous steps of cleaning and preprocessing the data, the cleaned EEG data for each participant and website was further processed. First, the cleaned data was annotated with specific time intervals corresponding to interactions with six websites: Quora, Pinterest, Spotify, LinkedIn, Instagram, and Facebook. These annotations were defined by onset times and durations (MNE 1.8.0 Documentation, 2024) (Antonenko *et al.*, 2010). The cleaned data with annotations was plotted to visualize the segments corresponding to different websites. Each data segment was cropped and labelled according to the specific website. By isolating the data segments, it was possible to conduct detailed examinations of the EEG responses to each specific website. The Friedman test, a non-parametric test was used to analyse differences in cognitive load across multiple treatment conditions when normality assumptions were violated. This test evaluated EEG data from participants on six different websites during account deletion processes, effectively handling non-normal data and assessing the impact of website conditions and EEG signal types on cognitive load (Sheil *et al.*, 2024). The mean peak amplitude for both Theta and Alpha waves was calculated across different websites to assess the variation in cognitive load induced by each site (Figure 2). These calculations were essential for comparing the cognitive load associated with "easy to cancel" versus "hard to cancel" websites. Additionally, the standard deviation for each of these measures was calculated to provide insights into the variability of the EEG responses, reflecting the consistency of cognitive load across different conditions (Freeman, 2004).

13 Eye-Tracking Data Preprocessing & Analysis

The data was cleaned by removing invalid data points and imputing the missing values using a linear interpolation technique. Noise was filtered to correct artifacts, including blinks, by applying a low-pass Butterworth filter of the 5th order with a 0.5 Hz cut-off, all using Python (Novák *et al.*, 2024, Yu *et al.*, 1999). The eye-tracking data were analysed by calculating two metrics: Average Fixation Duration and Time to First Fixation (within the area of interest (AOI)). The areas of interest (AOI) included the text above the sign-up button, which indicates the agreement to the Terms and Conditions (via a checkbox in the control condition). The dataset was filtered to isolate gaze points within the specified

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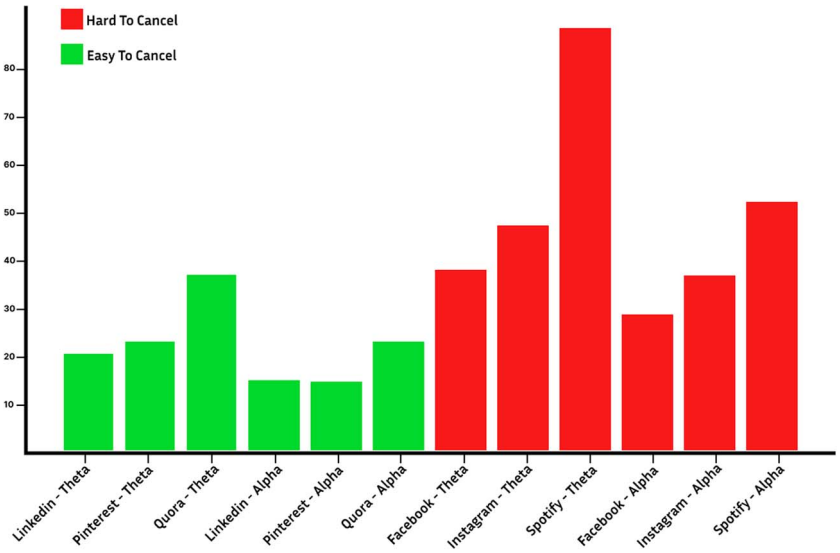

FIGURE 2. Comparison of mean peak amplitudes for easy vs. hard to cancel websites.

TABLE 1. Mean and standard deviation of theta and alpha waves in microvolt.

	Theta Mean	Theta Std	Alpha Mean	Alpha Std
Quora	35.34	11.01	22.11	4.34
Pinterest	21.69	8.83	13.88	1.68
Spotify	85.47	26.19	50.46	10.15
LinkedIn	19.28	7.5	14.32	2.13
Instagram	45.02	12.95	35.09	18.31
Facebook	36.8	13.94	27.53	7.18

TABLE 2. Average fixation duration mean and standard deviation in (ms).

Metrics	Media	Mean (ms)	Std (ms)
Average Fixation Duration	Eventbrite	2379	282
	Paypal	2143	134
	Salesforce	2879	128
	Linkedin	4436	131
	Facebook	4759	128
	Instagram	4569	143

AOI, and the Time to First Fixation values were calculated by measuring the mean time elapsed from when the user entered the webpage to the first fixation on the specified AOI. Average Fixation Duration was calculated by computing the mean of the total duration of all fixations (Si *et al.*, 2020). After preprocessing and cleaning the eye-tracking data, a statistical test was subsequently employed to analyse the results.A non-parametric methods were deemed more appropriate for further analysis. The Kruskal–Wallis H test (Table 3) was chosen to compare fixation durations and time to first fixation across the six websites (Peute *et al.*, 2015). This test determined if significant differences existed across these metrics (Mauri *et al.*, 2021). Additionally, websites were grouped into implicit (Facebook, Instagram, LinkedIn) and explicit (PayPal, Salesforce, Eventbrite) consent categories. The Mann–Whitney U test (Table 4) was used to compare time to first fixation between these groups, as it is suitable for non-normally distributed data (Mauri *et al.*, 2021). Descriptive statistics, including mean, standard deviation, were also calculated for average fixation durations and time to first fixation across the different media types (Razali & Wah, 2011). The mean and standard deviation for Time to First Fixation and Average Fixation Duration were calculated to assess participants' visual attention across different websites. Time to First Fixation measures the time taken by participants to first fixate on specific areas of interest (AOIs), providing insights into the immediacy of attention drawn by various elements on the webpage. Average Fixation Duration indicates the length of time participants spent focusing on these AOIs, reflecting the level of sustained attention (Lazar *et al.*, 2017).

TABLE 3. Time to first fixation mean and standard deviation in (ms).

Metrics	Media	Mean (ms)	Std (ms)
Time to First Fixation	Eventbrite	436	13
	Paypal	496	17
	Salesforce	483	11
	Linkedin	286	22
	Facebook	262	28
	Instagram	243	29

TABLE 4. Kruskal–Wallis statistical tests across all six websites.

Metrics	H-statistic	p-value
Average Fixation Duration	38.86	0.0046
Time to First Fixation	40.07	0.0032

14 Heatmaps

The Eye-tracking data were further analysed using visualisations generated by the Tobii Pro Lab software, which recorded participant gaze data and produced heat maps to signify the frequency and duration of gaze fixations. The areas of interest (AOI) included the text above the sign-up button, which indicates the agreement to the Terms and Conditions (via a checkbox in the control condition) (Drusch *et al.*, 2014).

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TABLE 5. Mann–Whitney U test for implicit vs. explicit consent.

Metrics	Mann–Whitney U	p-value
Average Fixation Duration	274.81	0.043
Time to First Fixation	280.72	0.029

TABLE 6. Sentiment analysis of platforms with explicit consent mechanism.

Sentiments	Negative	Neutral	Positive
	1.6	65.5%	32.9%

TABLE 7. Sentiment analysis of platforms with implicit consent mechanism.

Sentiments	Negative	Neutral	Positive
	10.6%	75.1%	14.3%

TABLE 8. Sentiment analysis of easy To cancel platforms.

Sentiments	Negative	Neutral	Positive
	2.3%	80.6%	17.1%

TABLE 9. Sentiment analysis of hard To cancel platforms.

Sentiments	Negative	Neutral	Positive
	16%	80.2%	3.8%

15 RTA Analysis

In addition, a Natural Language Processing (NLP) analysis was conducted on the transcribed interviews from the recorded RTA session to examine the sentiment used for both tasks. Text data was collected and processed using the NLTK library, with sentiment analysis performed using the VADER tool, which provided scores for positive, negative, neutral, and compound sentiments. The text was tokenized, and stop words were removed for further analysis. By combining eye tracking, EEG, and NLP analyses, this study offers an in depth understanding of how DPs in subscription processes affect user experience.

16 Results

EEG Data Findings The following sections present the results of the descriptive statistics, peak amplitude plots, Friedman hypothesis tests to study cognitive load.

16.1 Descriptive Statistics Results

Descriptive statistics in Table 2 represent the mean and standard deviation of Theta and Alpha waves across the six websites including Facebook, LinkedIn, Pinterest, Quora, Instagram, and Spotify.

16.2 Peak Amplitude Analysis

The mean peak amplitudes for Theta and Alpha waves were calculated across these six websites, as shown in the plot (Figure 2). The analysis revealed that the mean peak amplitudes for Theta waves were notably higher during interactions with Facebook, Spotify, and Instagram (Aftanas & Golocheikine, 2001, Liu, 2022).

17 RTA Analysis Results

The sentiment analysis provide a clear breakdown of user responses, categorizing them into positive, neutral, and negative sentiments. In the first task (Hard to Cancel), participants were familiar with the account deletion processes on Facebook and Instagram but were unfamiliar with those on Spotify and Quora.However, when it came to the Hidden Subscription task, all participants were familiar with the platforms involved.

18 Discussion on EEG findings

Hard to Cancel Platforms (Facebook, Spotify, Instagram), Platforms identified as Hard to Cancel, Facebook, Spotify, and Instagram, indicate higher Theta wave amplitudes compared to their Alpha wave amplitudes. This pattern suggests that these platforms require substantial cognitive engagement, particularly in decision making, problem solving, and cognitive control (Başar *et al.*, 1998, Fink & Benedek, 2014). Among these, Spotify shows the highest Theta amplitude, highlighting the platform's particularly demanding account deletion process. The elevated Theta activity also indicates that users must navigate complex interfaces requiring sensory integration and significant cognitive resources as supported by findings from the RTA sessions (Dustman *et al.*, 1999). Facebook similarly demonstrates high Theta activity, confirming that its multi steps account deletion process imposes heavy cognitive demands as also highlighted in the RTA sessions. Increased Alpha activity in Facebook, compared to Spotify and Instagram, may indicate moments of attentional relaxation during its interface navigation, potentially linked to familiar design elements as mentioned by participants in RTA sessions. Instagram, while also requiring high cognitive effort, presents slightly lower Theta amplitudes than Spotify and Facebook, which could reflect its more visually intuitive design (Berthouze *et al.*, 2010). Nonetheless, the significant Theta activity suggests a complex process that challenges users' executive functions, particularly during decision making tasks (Sheldon *et al.*, 1996) Easy-to-Cancel Platforms (Quora, Pinterest, LinkedIn). The easy-to-cancel platforms, including Quora, Pinterest, and LinkedIn, show consistently lower Theta and Alpha wave amplitudes. This suggests that these platforms impose minimal cognitive load during account deletion tasks (Sabate *et al.*, 2014). Their interfaces appear to provide straightforward navigation, reducing the need for extensive mental effort. While Pinterest displays slightly higher Theta activity compared to Quora and LinkedIn, this could be attributed to its visually rich content, which may momentarily engage cognitive functions related to visual processing. Comparison Between Hard and Easy Platforms Hard to cancel platforms consistently demand more cognitive resources, as evidenced by their higher Theta wave activity demands (Galin *et al.*, 1978, Sabate *et al.*, 2014). The multi-step processes in account deletion increase mental effort and attentional. Easy to cancel platforms, in contrast, provide a more streamlined experience, as reflected in their low Theta and Alpha amplitudes. This suggests that simplifying account deletion processes can reduce the cognitive burden on users, improving the overall user experience As users mentioned in the RTA sessions, the process of deleting an account was straightforward and very easy for them. While our findings suggest that transparent interface elements including clear consent mechanisms and explicit disclosures, can foster user trust and satisfaction, it is important to recognize that increased transparency does not always equate

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to improved usability in the short term. According to cognitive load theory (Steinfeld, 2016), presenting users with more detailed information or additional steps can temporarily elevate cognitive load, potentially introducing friction and reducing immediate user satisfaction. This tension is well documented in the UX literature, including the work of Cranor and colleagues, who have shown that privacy notices and consent banners, while essential for user rights and informed decision-making, can sometimes overwhelm users or disrupt task flow (Cranor, 2012, Skaramagkas *et al.*, 2021). Thus, designers must balance the long-term benefits of transparency and user protection with the need to minimize unnecessary mental effort and maintain a smooth user experience. Our results reinforce the importance of considering both cognitive and emotional impacts when implementing transparent design, and suggest that progressive disclosure or adaptive interfaces may help reconcile this trade-off.

19 Insights into "Hard to Cancel" Sentiment

The sentiment analysis of Instagram, Spotify, and Facebook reveals a shared theme of user frustration stemming from complex and confusing cancellation processes. For Instagram, users face a non intuitive and intricate process, with "confusing settings" and "many steps" leading to frustration despite the availability of online help. Spotify's cancellation experience is marked by significant dissatisfaction, with users encountering "buried settings" and "complicated" steps that feel intentionally designed to discourage cancellation, resulting in a higher negative sentiment. Similarly, Facebook's process is perceived as deliberately challenging, with "unclear" instructions and the need to "navigate multiple menus," contributing to a sense of frustration and difficulty. Based on the analysis of Instagram, Spotify, and Facebook, the sentiment generally shows a higher proportion of negative sentiments and a lower proportion of positive sentiments. The analysis highlights a common user dissatisfaction with the cancellation processes, indicating a need for these platforms to simplify and clarify their procedures to improve user experience and reduce frustration. The sentiment analysis of cancellation processes for Pinterest, Quora, and LinkedIn highlights a common theme of users experiencing a predominantly neutral sentiment, with appreciation for clear instructions. For Pinterest, users find the instructions clear and appreciate the straightforward process, with "no unnecessary steps". The emphasis on "reassured successful" indicates that users generally find the cancellation process smooth and manageable, with little cognitive burden involved. Similarly, Quora's and LinkedIn analysis shows a "user friendly interface" and clear instructions. The analysis generally shows a higher proportion of positive responses and a lower proportion of negative responses. This also highlights users' appreciation for clear instructions and straightforward cancellation processes, reflecting these platforms' success in making their procedures user-friendly and easy to navigate.

20 RQ1: Impact of "Hard to Cancel" Patterns on Cognitive Load

Therefore, the response to RQ1 is as follows. The EEG analysis reveals that "hard to cancel" patterns significantly increase cognitive load when compared to easier account deletion processes. Platforms such as Facebook, Spotify, and Instagram exhibit higher Theta and lower Alpha wave activity, indicating greater cognitive demands and mental effort. This heightened cognitive load is consistent with user reports of the complexity and frustration associated with cancelling accounts on these platforms. In contrast, platforms like LinkedIn, Pinterest, and Quora, which are easier to cancel, show lower cognitive load, as evidenced by more stable EEG patterns and user feedback suggesting a smoother, more straightforward experience. These findings emphasize the impact of complex account deletion processes on user cognitive load, highlighting the importance of intuitive and user-friendly design to reduce mental strain and improve the user experience.

21 Discussion on Eye-Tracking Findings

21.1 Time to first fixation

The analysis of the Time to First Fixation suggests that Eventbrite, PayPal, and Salesforce are more successful in quickly and consistently capturing user attention. This is due to the use of explicit consent mechanisms (checkboxes) on these platforms, which helps improve the visibility of terms and conditions for users. In contrast, Facebook, Instagram, and LinkedIn, Platforms with implicit consent mechanisms (no checkboxes) show shorter engagement times within the AIO, indicating less visibility of the terms and conditions on the AOI. Users on these platforms take longer to fixate on the AOI, likely due to the fine print and less prominent visibility of the Terms and Conditions section (Krafka *et al.*, 2016).

21.2 Average Fixation Duration

In terms of Average Fixation Duration, the data indicates that users fixate longer on the AOI on platforms with explicit consent mechanisms, specifically PayPal, Salesforce, and Eventbrite. Users spend more time engaged within the Terms and Conditions section, reflecting deeper interaction. Conversely, LinkedIn, Facebook, and Instagram, which utilize implicit consent, show shorter fixation durations within the AOI. This suggests that explicit consent mechanisms may enhance user attention and interaction with important information. The results indicate that LinkedIn's average fixation duration is significantly different from PayPal and is near significant when compared to Salesforce. This closeness in performance suggests that, despite LinkedIn and Salesforce following different consent mechanism approaches, LinkedIn's privacy policy section is almost as noticeable to users as Salesforce's. While LinkedIn's average fixation duration is shorter compared to platforms utilizing explicit consent mechanisms, it nonetheless exceeds the fixation durations observed on Facebook and Instagram, indicating a relatively higher level of user engagement with LinkedIn's privacy policy section. This nuance is important, as it shows that LinkedIn, while grouped with implicit consent platforms, does not perform as poorly as the other two in terms of user engagement. LinkedIn demonstrates slightly better performance. Overall, the study also highlights the importance of consent mechanisms (Menges *et al.*, 2020), as their design can significantly impact user interaction. Overall, while Eventbrite Salesforce and PayPal stand out for their effectiveness, platforms like Facebook, Instagram, and LinkedIn may require further optimization to enhance user engagement.

22 Heat map

The heatmaps for the sign-up pages of Facebook, Instagram, and LinkedIn clearly illustrate that users are not focusing their attention on the AOI (Figure 3). Visual attention is predominantly concentrated on the input fields and submission buttons, with minimal to negligible focus on the privacy policy section. Notably, LinkedIn shows a slight increase in user attention toward the

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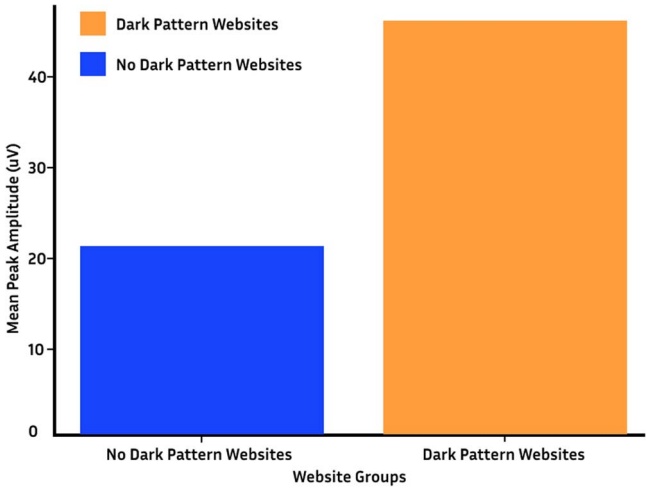

FIGURE 3. Comparison of mean peak amplitudes: no dark pattern vs. dark pattern websites.

privacy policy link compared to Facebook and Instagram. This increased focus on LinkedIn's privacy policy can be attributed to its proximity to the "Join Now" button and the larger text size, as mentioned in the RTA sessions as factors that captured users' attention more effectively. Additionally, the "Join Now" label serves as a strong call to action (CTA) button, clearly indicating to users that by clicking, they are actively joining the platform. However, the overall lack of focus on privacy policies across all three platforms suggests that these elements may not be prominently positioned or visually emphasized enough to engage users effectively. The heatmaps for the sign up pages of Salesforce, PayPal, and Eventbrite indicate that users are directing significant attention toward privacy policy sections (Figure 4). In Salesforce, participants mentioned in the RTA sessions that the checkbox made them curious and cautious about the privacy policy, prompting them to pay closer attention to this aspect of the website. Similarly, on PayPal's sign up page, the heatmap shows a more pronounced and focused attention on the privacy policy text, suggesting that users are particularly aware of and engaged with these elements. In the case of Eventbrite, the heatmap also highlights user focus on the privacy policy section (Figure 5). Participants in the RTA interviews noted that the bold text and different colour used for the privacy policy helped draw their attention, making them more likely to notice and consider this information. These findings suggest that the design choices made in these platforms including the use of bold text, colour differentiation, and strategic placement of checkboxes, effectively capture user attention and encourage them to engage with important legal and privacy information (McKight & Najab, 2010).

23 Mapping Design Elements to Cognitive Load and Attention

To increase the granularity of our findings, we identified which specific design features within the "hard to cancel" and "hidden subscription" flows were most strongly associated with measurable changes in cognitive load and visual attention, as detected by EEG and eye-tracking. Drawing on the Gray *et al.* dark patterns ontology, we identified several low-level interface elements that consistently triggered elevated cognitive load and attention shifts. For "hard to cancel" patterns, EEG data showed that multi-step cancellation flows, ambiguous or misleading wording (e.g., unclear labels for cancellation), and hidden or de-emphasized buttons (such as "cancel" links in fine print or low-contrast colors) were associated with increased alpha and theta activity, indicating greater mental effort and frustration. In the "hidden subscription" flows, eye-tracking revealed that pre-checked subscription boxes, fine print disclosures, and implicit consent mechanisms led to longer times to first fixation and shorter fixation durations on critical information, suggesting increased visual search effort and reduced clarity. These results demonstrate that specific, well-documented interface features, classified at the low level of the Gray *et al.* Ontology (Gray *et al.*, 2025), directly contributed to the observed cognitive and attentional impacts, providing a more precise understanding of how dark patterns affect user experience at the point of interaction.

24 Insights into "Hidden Subscription" Sentiment

The analysis of hidden subscription practices in Salesforce, PayPal, and Eventbrite highlights a strong emphasis on transparency, clarity, and user trust. Salesforce users value the prominence of informed consent, with themes like "transparent", "informed user", and "Trustworthy" reflecting a positive experience where subscription terms are clear and secure. PayPal similarly focuses on transparency and compliance, with users appreciating the "clarity" and "simplicity" built through detailed communication, ensuring "legal standards" are met. Eventbrite emphasizes simplicity and user control, with "clear", "concise," and "simplicity" being key themes that enhance user understanding (Mathur *et al.*, 2021). The sentiment analysis generally shows a higher proportion of positive responses and a lower proportion of negative responses,confirming that users had a positive experience. Overall, these platforms are recognized for their efforts in maintaining transparency and ensuring users are well informed about subscription terms, contributing to a positive and trustworthy user experience. Specific phrases like "insufficient feedback" and "lack of clarity" point to a lack of clear communication, making users feel unsure or mistrustful of their decisions. Overall, the analysis indicates a consistent experience across platforms where users feel they are being subtly manipulated into decisions due to the unclear presentation of information. When comparing implicit and explicit consent, LinkedIn, Instagram, and Facebook, with implicit consent, show higher levels of negative sentiment. Platforms that utilize explicit consent generally experience more positive user feedback (Negi & Mitra, 2020).

25 RQ2: The differences in user visual attention in the context of "Hidden Subscription" patterns

Therefore, the response to RQ2 is as follows. The research indicates that "hidden subscription" patterns significantly affect visual attention and user engagement, with a notable difference between platforms utilizing implicit and explicit consent mechanisms. Eye-tracking data shows that platforms with explicit consent mechanisms, such as Salesforce, PayPal, and Eventbrite, are more successful in capturing and maintaining user attention, particularly on critical elements like privacy policies and subscription terms. These platforms guide users effectively, leading to higher user engagement and a more transparent experience. In contrast, platforms relying on implicit consent, such as Instagram, Facebook, and LinkedIn, tend to capture user attention less effectively, resulting in slower engagement times and shorter fixation durations. This suggests

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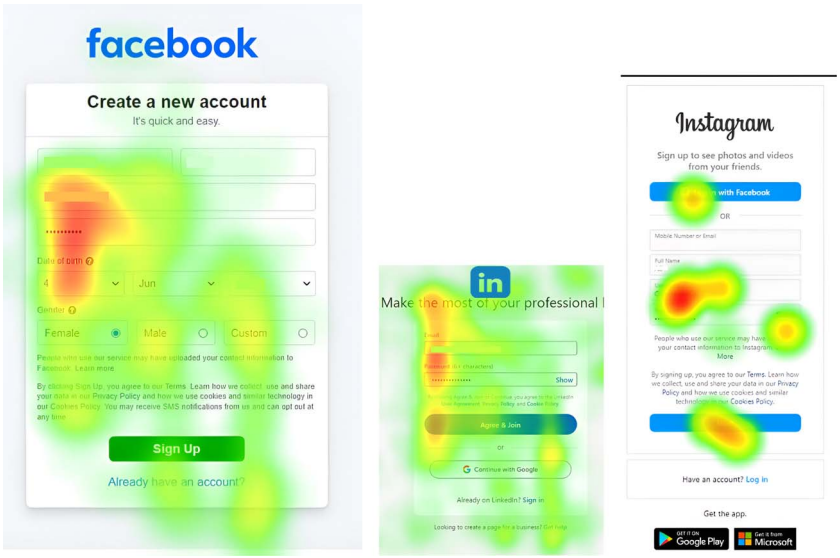

FIGURE 4. Platforms with implicit consent.

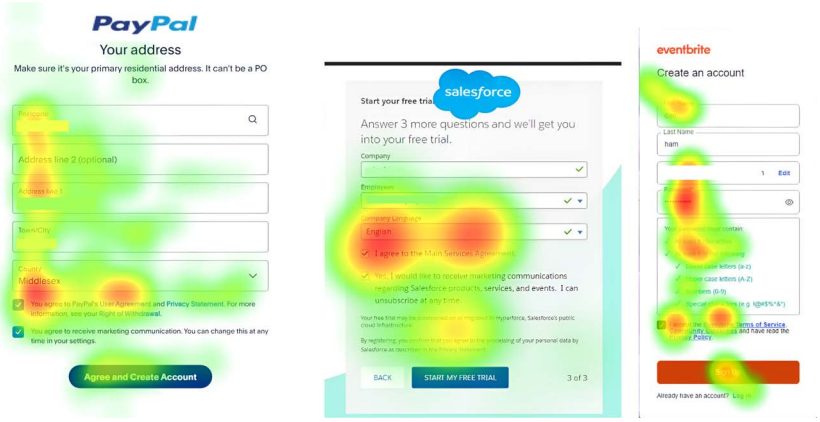

FIGURE 5. Platforms with explicit consent.

that users may struggle to find and focus on key information, leading to potential confusion and frustration. Therefore, hidden subscription patterns are more likely to negatively impact visual attention and user engagement on platforms using implicit consent, while explicit consent mechanisms appear to enhance user interaction and trust.

26 RQ3: Integrating EEG, Eye-Tracking, and Sentiment Analysis for a Holistic Understanding of Users' Interaction with Deceptive Patterns

EEG, eye-tracking, and sentiment analysis have been integrated to provide a holistic understanding of users' reactions to deceptive patterns by combining insights into cognitive load, visual attention, and emotional responses. EEG measures cognitive engagement and highlights the mental effort required to navigate complex interfaces, as seen in "hard to cancel" platforms with higher Theta wave activity. Eye-tracking identified how explicit consent mechanisms, influence visual attention and user interaction with privacy policies and Terms and Conditions section. Sentiment analysis complemented these findings by capturing users' emotional responses, revealing frustration with deceptive practices or appreciation for transparent and user-friendly designs. Together, these methods offer a comprehensive view of how deceptive patterns affect users cognitively, visually, and emotionally, guiding the development of ethical design strategies.

27 The Role of Interface Design in User Engagement and Cognitive Load

Overall, this study underscores the critical role of interface design in influencing user attention and engagement, particularly regarding consent mechanisms and privacy policy visibility. Platforms that employ explicit consent mechanisms with well-designed visual cues are more effective in capturing and sustaining user attention, leading to a more informed user experience. Conversely, platforms using implicit consent mechanisms may benefit from interface improvements to enhance user focus on important legal information. The comparison between explicit and implicit consent mechanisms highlights the importance of transparency and clear communication. Platforms that prioritize explicit consent not only improve user understanding and control but also foster a more trustworthy relationship with their users. The findings also indicate that the cognitive load imposed by these platforms is a crucial factor in user satisfaction, particularly in the context of account deletion processes. The findings suggest

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that reducing cognitive demands through better design could improve user experiences and reduce the negative impact of complex cancellation processes. Furthermore, the study suggests that familiarity with a platform may influence the user experience, potentially affecting cognitive load and how easily users interact with its features. These findings emphasize the importance of designing user friendly cancellation processes that minimize cognitive load and frustration. By addressing the pain points identified in the more challenging platforms (Spotify, Facebook, and Instagram), designers can enhance user satisfaction and build trust, ultimately contributing to a more positive overall user experience. The insights gained from this analysis serve as a crucial reference for improving account management practices across digital platforms, highlighting the need for ongoing evaluation and refinement of user interaction strategies.

28 Limitations and Future Research

Despite the significant findings, this study is not without limitations. First, the research was conducted exclusively on web-based platforms accessed via desktop or laptop computers, limiting the generalizability of the results to mobile or other digital interfaces. Additionally, the study focused on a limited set of the patterns; future research could expand on these findings by exploring other DPs and considering additional contextual factors such as user demographics and the influence of mobile versus desktop interfaces. Employing advanced EEG technology, such as gel-based caps, could also enhance the accuracy of cognitive load measurements. While this study offers a novel approach to explore deceptive patterns, several limitations must be acknowledged. First, the participant pool consisted entirely of Master's students from a single institution, which may limit the generalizability of findings. This group likely possesses higher digital literacy and familiarity with web-based interfaces than the general population, potentially reducing the observed cognitive burden compared to less experienced or older users. Future research should aim to include a more demographically diverse sample, including participants of varied age ranges, education levels, and cultural backgrounds to test how different user groups perceive and respond to deceptive patterns. Second, all tasks in this study were conducted on desktop computers in a controlled lab environment, which offered consistency in experimental setup but may not reflect the diversity of real-world usage scenarios. Although we acknowledge that mobile interfaces may offer distinct user experiences, especially in terms of layout, gesture-based navigation, and visibility constraints, this study focused on desktop platforms for standardization purposes. Future work should explore the effects of deceptive patterns on mobile and tablet interfaces, where interface constraints and touch interactions may amplify or alter user responses. Finally, the study involved simulated user accounts with no real financial or personal data at stake. While this ensured participant privacy and ethical compliance, it may have reduced emotional engagement or urgency, particularly in cancellation tasks. Future research could explore higher-stakes scenarios or employ longitudinal methods to capture the persistence of frustration or decision regret over time.

29 Conclusion

This study highlights the critical influence of user interface design on cognitive load, user engagement, and sentiment, with a particular focus on "Hard to Cancel" and "Hidden Subscription". The research found that platforms with more complex cancellation processes impose higher cognitive demands on users, as evidenced by increased Theta wave activity and decreased Alpha wave activity. These neural indicators suggest that users experience greater mental effort and frustration during the account deletion process on these platforms. Furthermore, the study underscores the pivotal role of consent mechanisms in shaping user attention and engagement. Platforms that employ explicit consent mechanisms were found to be more effective in capturing and maintaining user attention, leading to higher engagement with critical legal and privacy information. In contrast, platforms that rely on implicit consent, were observed to elicit slower user engagement and diminished focus on terms and conditions, resulting in a less informed and less engaged user experience. The sentiment analysis conducted further revealed that platforms with clear and explicit consent mechanisms foster a more positive user experience and stronger user relationships. One practical and recurring usability issue observed during our study was the ineffectiveness of platform search functionalities in helping users locate account deletion options. Even when users actively searched for "delete account" or "cancel subscription," the search bars often returned irrelevant or buried results. A strong recommendation is for platforms to implement robust information retrieval systems that support direct user intent and do not obscure cancellation flows (Rosner & Grove, 1999). Furthermore, we suggest the introduction of universal design standards or regulatory requirements across digital platforms that mandate a clearly labeled and consistently located section for account cancellation and subscription management. This would reduce confusion, prevent fatigue-based abandonment, and support user autonomy by ensuring that account closure is not hidden behind complex or buried settings. For hidden subscription patterns, it is essential that platforms adopt clear, visible, and contextually prominent language when asking for consent. Interfaces should avoid small font sizes, greyed-out text, or misleading placement of checkboxes. Instead, platforms should explore creative yet ethical ways to draw user attention to the implications of their consent through brief tooltips, concise warnings, or modal confirmations before submission. These mechanisms help prevent users from unknowingly opting in due to habituation or visual distraction. Implementing these recommendations not only addresses persistent usability and ethical challenges but also sets a foundation for future research and policy aimed at fostering more transparent, user-centered digital environments. Although our findings underscore the cognitive and emotional benefits of transparent and user-centered design, it is important to recognize that practical implementation is often shaped by business models, regulatory requirements, and the need to balance transparency with usability. As Leiser and Santos (Lehtinen *et al.*, 2008) note, commercial pressures can incentivize the use of manipulative or obstructive patterns, and even well-intentioned ethical interventions including explicit consent mechanisms can introduce friction or complicate user trust. These trade-offs highlight the complex realities faced by designers and organizations, who must navigate between protecting user rights and achieving business objectives. Our results should therefore be interpreted as supporting the pursuit of ethical design within these constraints, rather than as advocating for universally idealized solutions. Finally, regulatory bodies should consider setting minimum standards for consent communication design including minimum font size, contrast ratios, and positioning of key legal terms to reduce manipulation through visual hierarchy tricks including false hierarchy or fine print placement. Designers should be discouraged from relying on passive or defaulted

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consent mechanisms and encouraged to prioritize transparency, clarity, and the user's right to make an informed decision.

Data Availability

The data underlying this article cannot be shared publicly due to the privacy of individuals that participated in the study. The data will be shared on reasonable request to the corresponding author.

Conflict of Interest

The authors declare that there are no conflicts of interest related to this work.

References

Aftanas, L. I., & Golocheikine, S. A. (2001). Human anterior and frontal midline theta and lower alpha reflect emotionally positive state and internalized attention: high-resolution eeg investigation of meditation. *Neuroscience Letters*, **310**, 57–60. https://doi.org/10.1016/S0304-3940(01)02094-8.

Antonenko, P., Paas, F., Grabner, R., & Van Gog, T. (2010). Using electroencephalography to measure cognitive load. *Educational Psychology Review*, **22**, 425–438. https://doi.org/10.1007/s10648-010-9130-y.

Başar, E., Rahn, E., Demiralp, T., & Schürmann, M. (1998). Spontaneous eeg theta activity controls frontal visual evoked potential amplitudes. *Electroencephalography and Clinical Neurophysiology/Evoked Potentials Section*, **108**, 101–109. https://doi.org/10.1016/S0168-5597(97)00039-7.

Bazanova, O., & Vernon, D. (2014). Interpreting eeg alpha activity. *Neuroscience & Biobehavioral Reviews*, **44**, 94–110. https://doi.org/10.1016/j.neubiorev.2013.05.007.

Berthouze, L., James, L. M., & Farmer, S. F. (2010). Human eeg shows long-range temporal correlations of oscillation amplitude in theta, alpha and beta bands across a wide age range. *Clinical Neurophysiology*, **121**, 1187–1197. https://doi.org/10.1016/j.clinph.2010.02.163.

Bongard-Blanchy, K., Rossi, A., Rivas, S., Doublet, S., Koenig, V., & Lenzini, G. (2021) "I am definitely manipulated, even when I am aware of it. It's ridiculous!"—dark patterns from the end-user perspective. In *Proceedings of the 2021 ACM Designing Interactive Systems Conference*, pp. 763–776.

Brignull, H. (2019) Dark patterns. In *Dark Patterns*.

Brignull, H. (2023). *Deceptive Patterns: Exposing the Tricks Tech Companies Use to Control You.*.

Cranor, L. F. (2012). Necessary but not sufficient: standardized mechanisms for privacy notice and choice. *Journal on Telecommunications and High Technology Law*, **10**, 273.

Del Percio, C., Lopez, S., Noce, G., Lizio, R., Tucci, F., Soricelli, A., Ferri, R., Nobili, F., Arnaldi, D., Famà, F.*et al.* (2023). What a single electroencephalographic (eeg) channel can tell us about Alzheimer's disease patients with mild cognitive impairment. *Clinical EEG and Neuroscience*, **54**, 21–35. https://doi.org/10.1177/15500594221125033.

Drusch, G., Bastien, J., & Paris, S. (2014). Analysing eye-tracking data: from scanpaths and heatmaps to the dynamic visualisation of areas of interest. *Advances in Science, Technology, Higher Education and Society in the Conceptual Age: STHESCA*, **20**, 25.

Dustman, R. E., Shearer, D. E., & Emmerson, R. Y. (1999). Life-span changes in eeg spectral amplitude, amplitude variability and mean frequency. *Clinical Neurophysiology*, **110**, 1399–1409. https://doi.org/10.1016/S1388-2457(99)00102-9.

Fink, A., & Benedek, M. (2014). Eeg alpha power and creative ideation. *Neuroscience & Biobehavioral Reviews*, **44**, 111–123. https://doi.org/10.1016/j.neubiorev.2012.12.002.

Fogg, B. J. (1998). Persuasive computers: perspectives and research directions. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 225–232.

Freeman, W. J. (2004). Origin, structure, and role of background eeg activity. Part 1. Analytic amplitude. *Clinical Neurophysiology*, **115**, 2077–2088. https://doi.org/10.1016/j.clinph.2004.02.029.

Galin, D., Johnstone, J., & Herron, J. (1978). Effects of task difficulty on eeg measures of cerebral engagement. *Neuropsychologia*, **16**, 461–472. https://doi.org/10.1016/0028-3932(78)90069-6.

Gomes, I., Pereira, I., Soares, I., Antunes, M., & Au-Yong-Oliveira, M. (2021) Keeping the beat on: a case study of spotify. In *Trends and Applications in Information Systems and Technologies: Volume 2 9*, pp. 337–352. Springer.

Gray, C. M., Chen, J., Chivukula, S. S., & Qu, L. (2021a). End user accounts of dark patterns as felt manipulation. *Proceedings of the ACM on Human–Computer Interaction*, **5**, 1–25. https://doi.org/10.1145/3479516.

Gray, C. M., Santos, C., Bielova, N., Toth, M., & Clifford, D. (2021b) Dark patterns and the legal requirements of consent banners: an interaction criticism perspective. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, pp. 1–18.

Gray, C. M., Santos, C. T., Bielova, N., & Mildner, T. (2024) An ontology of dark patterns knowledge: foundations, definitions, and a pathway for shared knowledge-building. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*, pp. 1–22.

Gray, C. M., Mildner, T., & Gairola, R. (2025) Getting trapped in amazon's "iliad flow": a foundation for the temporal analysis of dark patterns. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*, pp. 1–10.

Guan, Z., Lee, S., Cuddihy, E., & Ramey, J. (2006). The validity of the stimulated retrospective think-aloud method as measured by eye tracking. In *Proceedings of the SIGCHI conference on Human Factors in computing systems*, 1253–1262.

Ibarra, I. A. (2017). *Should we treat data as labor? Moving beyond 'free'*. SSRN.

Ifeachor, E. C., & Jervis, B. W. (2002). *Digital Signal Processing: A Practical Approach*. Pearson Education.

Jamalifard, M., Russell-Rose, T., & Brignull, H. (2024). *Exploring Deceptive Patterns: Insights From Eye Tracking, EMG and Sentiment Analysis*.

Kirsh, D., & Maglio, P. (1994). On distinguishing epistemic from pragmatic action. *Cognitive Science*, **18**, 513–549. https://doi.org/10.1207/s15516709cog1804_1.

Klimesch, W. (1999). Eeg alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain Research Reviews*, **29**, 169–195. https://doi.org/10.1016/S0165-0173(98)00056-3.

Krafka, K., Khosla, A., Kellnhofer, P., Kannan, H., Bhandarkar, S., Matusik, W., & Torralba, A. (2016). Eye tracking for everyone. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2176–2184.

van der Laan, L. N., Hooge, I. T., De Ridder, D. T., Viergever, M. A., & Smeets, P. A. (2015). Do you like what you see? The role of first fixation and total fixation duration in consumer choice. *Food Quality and Preference*, **39**, 46–55. https://doi.org/10.1016/j.foodqual.2014.06.015.

Lazar, J., Feng, J. H., & Hochheiser, H. (2017). *Research Methods in Human–Computer Interaction*. Morgan Kaufmann.

Lehtinen, M., Happonen, A., & Ikonen, J. (2008) Accuracy and time to first fix using consumer-grade GPS receivers. In *2008 16th*

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International Conference on Software, Telecommunications and Computer Networks, pp. 334–340. IEEE.

Leiser, M., & Santos, C. (2023). *Dark Patterns, Enforcement, and the Emerging Digital Design Acquis: Manipulation Beneath the Interface*.

Liu, B. (2022). *Sentiment Analysis and Opinion Mining*. Springer Nature.

Luck, S. J., & Gaspelin, N. (2017). How to get statistically significant effects in any ERP experiment (and why you shouldn't). *Psychophysiology*, **54**, 146–157. https://doi.org/10.1111/psyp.12639.

Luguri, J., & Strahilevitz, L. J. (2021). Shining a light on dark patterns. *Journal of Legal Analysis*, **13**, 43–109. https://doi.org/10.1093/jla/laaa006.

Maier, M., & Harr, R. (2019). Dark patterns—an end user perspective. **16**, 170–199. https://doi.org/10.17011/ht/urn.202008245641.

Mathur, A., Acar, G., Friedman, M. J., Lucherini, E., Mayer, J., Chetty, M., & Narayanan, A. (2019) Dark patterns at scale: findings from a crawl of 11k shopping websites. In *Proceedings of the ACM on Human–Computer Interaction, 3(CSCW)*, pp. 1–32.

Mathur, A., Kshirsagar, M., & Mayer, J. (2021) What makes a dark pattern... dark? Design attributes, normative considerations, and measurement methods. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, pp. 1–18.

Mauri, M., Rancati, G., Gaggioli, A., & Riva, G. (2021). Applying implicit association test techniques and facial expression analyses in the comparative evaluation of website user experience. *Frontiers in Psychology*, **12**, 674159. https://doi.org/10.3389/fpsyg.2021.674159.

McKight, P. E., & Najab, J. (2010). Kruskal–Wallis test. *The Corsini Encyclopedia of Psychology*, 1–1. https://doi.org/10.1002/9780470479216.corpsy0491.

Menges, R., Kramer, S., Hill, S., Nisslmueller, M., Kumar, C., & Staab, S. (2020). A visualization tool for eye tracking data analysis in the web. In *ACM Symposium on Eye Tracking Research and Applications*, 1–5.

Negi, S., & Mitra, R. (2020). Fixation duration and the learning process: an eye tracking study with subtitled videos. *Journal of Eye Movement Research*, **13**. https://doi.org/10.16910/jemr.13.6.1.

Nouwens, M., Liccardi, I., Veale, M., Karger, D., & Kagal, L. (2020) Dark patterns after the gdpr: scraping consent pop-ups and demonstrating their influence. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pp. 1–13.

Novák, J. Š., Masner, J., Benda, P., Šimek, P., & Merunka, V. (2024). Eye tracking, usability, and user experience: a systematic review. *International Journal of Human–Computer Interaction*, **40**, 4484–4500.

Ouzts, A. D., & Duchowski, A. T. (2012). Comparison of eye movement metrics recorded at different sampling rates. In *Proceedings of the Symposium on Eye Tracking Research and Applications*, 321–324.

Perrin, F., Pernier, J., Bertrand, O., & Echallier, J. F. (1989). Spherical splines for scalp potential and current density mapping. *Electroencephalography and Clinical Neurophysiology*, **72**, 184–187. https://doi.org/10.1016/0013-4694(89)90180-6.

Peute, L. W., de Keizer, N. F., & Jaspers, M. W. (2015). The value of retrospective and concurrent think aloud in formative usability testing of a physician data query tool. *Journal of Biomedical Informatics*, **55**, 1–10. https://doi.org/10.1016/j.jbi.2015.02.006.

Razali, N. M., Wah, Y. B.*et al.* (2011). Power comparisons of Shapiro–Wilk, Kolmogorov–Smirnov, Lilliefors and Anderson–Darling tests. *Journal of Statistical Modeling and Analytics*, **2**, 21–33.

Rosner, B., & Grove, D. (1999). Use of the Mann–Whitney u-test for clustered data. *Statistics in Medicine*, **18**, 1387–1400. https://doi.org/10.1002/(SICI)1097-0258(19990615)18:11\(\(\)1387::AID-SIM126\(\)\)3.0.CO;2-V.

Russell-Rose, T., & Makri, S. (2012) Designing for consumer search behaviour. In *Proceedings of the Symposium on Human–Computer Interaction and Information Retrieval*.

Sabate, F., Berbegal-Mirabent, J., Cañabate, A., & Lebherz, P. R. (2014). Factors influencing popularity of branded content in facebook fan pages. *European Management Journal*, **32**, 1001–1011. https://doi.org/10.1016/j.emj.2014.05.001.

Sandkühler, S., & Bhattacharya, J. (2008). Deconstructing insight: Eeg correlates of insightful problem solving. *PLoS One*, **3**, e1459. https://doi.org/10.1371/journal.pone.0001459.

Sheil, A., Acar, G., Schraffenberger, H., Gellert, R., & Malone, D. (2024) Staying at the roach motel: cross-country analysis of manipulative subscription and cancellation flows. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*, pp. 1–24.

Sheldon, M. R., Fillyaw, M. J., & Thompson, W. D. (1996). The use and interpretation of the Friedman test in the analysis of ordinal-scale data in repeated measures designs. *Physiotherapy Research International*, **1**, 221–228. https://doi.org/10.1002/pri.66.

Si, Y., Li, F., Duan, K., Tao, Q., Li, C., Cao, Z., Zhang, Y., Biswal, B., Li, P., Yao, D., & Xu, P. (2020). Predicting individual decision-making responses based on single-trial eeg. *NeuroImage*, **206**, 116333. https://doi.org/10.1016/j.neuroimage.2019.116333.

Skaramagkas, V., Giannakakis, G., Ktistakis, E., Manousos, D., Karatzanis, I., Tachos, N. S., Tripoliti, E., Marias, K., Fotiadis, D. I., & Tsiknakis, M. (2021). Review of eye tracking metrics involved in emotional and cognitive processes. *IEEE Reviews in Biomedical Engineering*, **16**, 260–277.

Steinfeld, N. (2016). "i agree to the terms and conditions": (how) do users read privacy policies online? An eye-tracking experiment. *Computers in Human Behavior*, **55**, 992–1000. https://doi.org/10.1016/j.chb.2015.09.038.

Sweller, J. (1988). Cognitive load during problem solving: effects on learning. *Cognitive Science*, **12**, 257–285. https://doi.org/10.1207/s15516709cog1202_4.

Waldman, A. E. (2020). Cognitive biases, dark patterns, and the 'privacy paradox'. *Current Opinion in Psychology*, **31**, 105–109. https://doi.org/10.1016/j.copsyc.2019.08.025.

Yao, D. (2001). A method to standardize a reference of scalp eeg recordings to a point at infinity. *Physiological Measurement*, **22**, 693–711. https://doi.org/10.1088/0967-3334/22/4/305.

Yu, B., Gabriel, D., Noble, L., & An, K.-N. (1999). Estimate of the optimum cutoff frequency for the butterworth low-pass digital filter. *Journal of Applied Biomechanics*, **15**, 318–329. https://doi.org/10.1123/jab.15.3.318.

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