Dark patterns in consent statements

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Master Science Thesis

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Abstract

Dark patterns are design nudges that steer peoples' behaviour in an unconscious way through persuasive interface design. Increasingly found in privacy consent statements, they possibly undermine principles of the new General Data Protection Regulation (GDPR) of the EU, which aim at giving users control over their personal data, assuming that people engage in consent statements in a rational and deliberate manner. This online study ($N = 228$) investigated whether three of the most common dark patterns (default, aesthetic manipulation, obstruction) lead users to choose a privacy-unfriendly option over a privacy-friendly one, even if the latter one is rationally superior. Further, it was examined if the aforementioned dark patterns decrease users' perception of control over their personal data in consent statement situations. Although the majority of participants always chose the privacy-unfriendly option and reported a lack of control over their personal data, we did not find clear support for this being due to the design nudges. Using mixed-effects modelling, only obstruction showed a marginally significant effect in the expected direction on the consent decision. Regarding perceived control, again only obstruction displayed a significant effect, however, this time in the opposite direction as expected. Overall, our findings support the notion that the current consent model does not work as intended and give insights into why this might be the case.

Keywords: dark patterns; privacy; design nudges; GDPR; consent statements

The General Data Protection Regulation (GDPR) of the European Union entered into force on May 25th, 2018 to regulate the processing of personal data and entitle online users to their right of privacy (Council of the European Union, 2016). Concretely, the goal is that “natural persons should have control of their personal data” (Council of the European Union, 2016, p. 2, Recital 7). The necessity of this was exemplified by recent incidents of the misuse of personal data such as the Facebook-Cambridge Analytica scandal, where information from millions of Facebook users was utilised for political micro-targeting (Granville, 2018).

One key mechanism to give people control over their personal data are consent statements, which are legal documents that a) inform users how their data are processed, and b) ask for their consent (this system is called notice and choice model). To ensure that users understand the decision they make with a consent statement, GDPR set up criteria to define what giving consent should look like. These criteria include that “consent should be given by a clear affirmative act establishing a freely given, specific, informed and unambiguous indication of the data subject’s agreement to the processing of personal data. . . ” (Council of the European Union, 2016, p. 6, Recital 32). In that, GDPR assumes that people engage in consent statements in a conscious and deliberate manner when making privacy decisions. This corresponds to a prominent model of privacy decision making, the privacy calculus theory, which presumes peoples’ behaviour to be fundamentally rational and privacy decisions to be made through conscious weighing of the costs and benefits of each choice option. But does GDPR lead in practice to consent statements where people perceive control over their personal data, as well as where people show deliberate, rational decision behaviour?

This is questionable in light of a new trend of using so-called “dark patterns” in consent statements, which aim to influence users’ privacy decisions (Forbrukerrådet, 2018). Dark patterns are understood as design nudges, which steer users towards a certain choice through persuasive interface design (Brignull, n.d.; Gray, Kou, Battles, Hoggatt, & Toombs, 2018). Nudging means influencing the decisions of individuals or groups through minor changes in the choice environment without compromising freedom of choice (a prominent example is a fly painted on an urinal in a public men’s toilet to prevent urine spillage; Thaler & Sunstein, 2009). The use of dark patterns (and nudges in general) can be ethically problematic because it may lead users to make choices that are not in their interest and deprive users from their perceived control (Forbrukerrådet, 2018; Schubert, 2015). Furthermore, it is debatable whether these practices follow GDPR’s principles of data protection by design and data protection by default, which aim at data minimisation (Council of the European Union, 2016, p. 15, Recital 78).

GDPR as well as the privacy calculus theory view privacy decisions to be made by what Kahneman (2011) calls System 2, that is the consciously reasoning part of us. However, considering evidence from a multi-disciplinary literature assessment from Acquisti et al. (2017), it cannot be assumed that people behave purely rationally in privacy decision situations, but rather apply heuristics - that is mental shortcuts in decision making - and fall back to cognitive or behavioural biases, which work rather on the intuitive, heuristic System 1 (Sunstein, 2016a).

Consent statements feature several characteristics that make them prone to applying heuristics. For one, there is an information asymmetry between the user confronted with the consent statement and the data processing party asking for it. The user has access to less information regarding the purpose of data collection as well as possible future usage of it than the data processing party. Secondly, consent statements are often ambiguous in their language (e.g., the data *may* be used for a certain cause) creating a decision under uncertainty for the user because not all possible outcomes are known. Acquisti et al. (2017) argue that specifically these circumstances facilitate the application of heuristics, given that human rationality is limited to the available cognitive resources as well as the available time (based on the concept of bounded rationality; Simon, 1957).

Further, there are several cognitive biases such as the status-quo-bias (individuals' preference for default choices) or the salience-bias (people tend to focus on more prominent features), which come into play in any decision process and thus also in consent statement situations. The aforementioned characteristics of consent statements in combination with cognitive biases are likely to facilitate the mechanism of dark patterns, which targets mainly the intuitive, heuristic System 1 (Mirsch, Lehrer, & Jung, 2017; Sunstein, 2016a). In sum, design nudges such as dark patterns aim at triggering non-rational user behaviour and consent statements seem to provide a suitable context for this.

While there are many examples of the use of dark patterns in practice (see Brignull, n.d.; Fansher, Chivukula, & Gray, 2018; Forbrukerrådet, 2018), the field of privacy and data protection lacks research in this regard. It is crucial to assess whether a) the understanding of privacy decision making of GDPR and of the privacy calculus theory (i.e., people think rationally and deliberately about privacy decisions) represents reality and b) whether GDPR guidelines give users control over their personal data (we interpret it here as perceive control). Our two research aims are thus to investigate: given a consent statement situation with two options (privacy-friendly vs. privacy-unfriendly), do dark patterns lead users to choose the privacy-unfriendly option more often than the privacy-friendly option, even if the privacy friendly option is rationally superior? And do dark patterns deprive users from their perceived control over their personal data?

The current study addresses these aims by running an online experiment to investigate how three of the most common dark patterns (Fansher et al., 2018), that is (1) default, (2) aesthetic manipulation and (3) obstruction, influence users' decisions as well as their level of perceived control in consent statement situations. Default refers to any situation where one option is preselected prior to any action of the user, for example when the option to agree to a privacy policy is selected by default (Gray et al., 2018). Aesthetic manipulation refers to the act of giving "one option visual or interactive precedence over others", for example when one out of two choice buttons is coloured blue while the other one is simply grey (also called "false hierarchy"; Gray et al., 2018, p. 7). Obstruction means making an interaction more difficult than it needs to be to dissuade the user from a certain action or choice, for example when the option to opt-out of online tracking is not presented together with the opt-in option but can only be reached by clicking through several submenus. Even though these nudging principles could be used either way, in the context of dark patterns they always mean nudging towards the privacy-unfriendly option.

Following this nudge (choosing the privacy-unfriendly option) can be considered a non-rational choice if the privacy-friendly option bears greater utility in terms of costs and benefits (i.e., rationally superior) than the privacy-unfriendly option (Archer, 2013). In the context of our study this means that the privacy-unfriendly option (i.e., allowing web tracking) bears the cost of potentially losing control over one's personal data without providing any benefit (such as more relevant advertising). Hence rational choice theory would predict the privacy-friendly option to be chosen in this case (Smith, Dinev, & Xu, 2011). Deviations from this prediction indicate that people engage in privacy decisions (in the context of consent statements) rather through the automatic, heuristic System 1 than the rational, deliberate System 2.

However, there are also other factors which may influence whether a person acts in a rather fast and heuristic or more deliberate manner on privacy decisions. Evidence from previous research suggests that individual privacy concerns influence users' privacy decisions in general (Awad & Krishnan, 2006; Malhotra, Kim, & Agarwal, 2004) as well as specifically in the context of design nudges in consent statements (Lai & Hui, 2006). Lai and Hui (2006) found that people with higher privacy concerns were less likely to be swayed by a default setting in a consent statement than people with lower privacy concerns. The researchers gave as a possible explanation that people with higher privacy concerns may study the available options more carefully and deliberate more about their choice. Therefore, we included individual privacy concerns as a control variable.

We hypothesised that in a consent statement situation with two choice options (privacy-friendly vs. privacy-unfriendly), where the privacy-friendly option is rationally superior,

> Hypotheses 1a/b/c: participants will be more likely to choose the privacy-unfriendly option (compared to privacy-friendly), when the privacy-unfriendly option is (H1a) preselected, (H1b) visually more salient or (H1c) the alternative (privacy-friendly) option is obstructed.

> Hypotheses 2a/b/c: participants report lower levels of perceived control over their personal data when the privacy-unfriendly option is (H2a) preselected, (H2b) visually more salient or (H2c) the alternative (privacy-friendly) option is obstructed.

Because little is known about the effects of dark patterns in consent statements, this pioneer study focused on their main effects rather than possible (and more speculative) interaction or moderation effects, in order to create a solid basis for further investigation. Nevertheless, we repeatedly highlighted the role of deliberation as an indicator of System 2 behaviour. Little conscious deliberation, on the other hand, is associated with heuristic decision making (Albar & Jetter, 2009) and, in that, linked to System 1 behaviour, which dark patterns seem to target. Therefore, we investigated for exploratory purposes the possible moderating role of deliberation in the decision process. We hypothesised that more deliberation would reduce the effects of the design nudges on the outcomes consent decision and level of perceived control.

Method

Before running our online experiment, we preregistered our sample size estimation, hypotheses and statistical analysis. The preregistration, the code of the study application, all used materials, data, and analysis scripts (information about the used R version as well as all packages can be found in Appendix A) are available on the Open Science Framework (https://osf.io/c7qza/).

Procedure and Design

The online experiment followed a within-subjects design where participants were asked to review eight news websites (shown in a random order) and report on their first impression of the visual design of each news website (this cover story was used to create a realistic setting for the presentation of consent statements and disguise the true purpose of the study).

Before showing each news website, a consent statement was displayed, offering two choice possibilities: allow the website and other third parties data collection and web tracking (privacy-unfriendly) versus not allowing the website and other third parties data collection and web tracking (privacy-friendly). After making a choice for the consent statement, the news website was shown (no matter which option the participant had selected) but only for three seconds to fit the cover story about first impressions. Each news website was followed by three questions about the participant's first impression of the design of the news website (for the sake of the cover story). After reviewing all news websites (which corresponds to part 1 of the study), the eight consent statements were presented again (one by one in the form of screenshots) and participants were asked how much control they felt each consent statement gave them over their personal information as well as how much they had deliberated on the decision. Additionally, for each consent statement (presented as a screenshot) manipulation check questions were asked about whether they had read the consent information and could recall the option they had chosen. Lastly, individual privacy concerns were assessed (only once for each participant) and control questions about individual browser setup and device type asked. At the end of the study, participants were debriefed about the cover story and the true purpose of the experiment.

Website and Materials

Website. To run our online experiment, we set up a website using the Python framework Flask (Lord, Mönnich, Ronacher, & Unterwaditzer, 2010). The study application was hosted on a Radboud University server. To test the credibility of our cover story, a preliminary pilot study was conducted. Four bachelor students were asked to do the study while thinking aloud, showing that the cover story worked as intended. We used eight different news website templates, which are licensed under the Creative Commons Attribution 3.0 (Colorbib, 2019). The news websites were called *Avision* (Figure C1), *Megazine* (Figure C2), *Motivemag* (Figure C3), *Quitelight* (Figure C4), *Techmag* (Figure C5), *Technews* (Figure C6), *Viral* (Figure C7) and *Webmag* (Figure C8). The templates were partly adjusted in functionality (e.g., hyperlinks were disabled), content (e.g., exchange placeholder text such as "lorem ipsum" with plausible news content) and design to fit the purpose of our study. To achieve additionally required functionality for the online experiment, such as building multi-step consent statements (i.e., obstruction manipulation) or detecting when participants clicked on the back button, we used code solutions from An (2019) and Brooke (2011), respectively, which are available under the MIT license.

Consent Statements. For each news website we created a consent statement, which appeared when a participant was directed to the news website. The general layout and text of the consent statements was inspired by a corpus consisting of consent statements of several popular news websites as well as of big tech-companies (corpus available on OSF). The aim was to create "universal" consent statements, which represent a majority of the consent statements used in practice. Whereas the main characteristics (e.g., content of the provided text) of the consent statements were constant across all conditions, we changed minor design details (e.g., font type, order of the sentences in the text, colour of the consent box edges etc.) of each consent statement to make them look not identical and support the cover story about eight independent, external news websites. To have an indication of non-rational behaviour, the consent statements provided no information about any benefit of choosing the privacy-unfriendly option "Agree" (e.g., better targeted advertising), which only left the cost of potentially losing control over ones' personal data when agreeing to the policy (i.e., allowing web tracking). Hence, choosing the privacy-unfriendly option "Agree" was considered a non-rational choice (one example consent information text can be found in Appendix B).

Whereas the general layout of the consent statements was consistent, each statement contained one out of eight possible combinations of the three dark patterns (1) default, (2) aesthetic manipulation and (3) obstruction. The statistical model we used (mixed-effects model) required the inclusion of all possible combinations of the independent variables (i.e., the dark patterns) to accurately estimate the effect of each individual predictor. Default was represented by a preselected "Agree" radio button on the websites *Quitelight*, *Techmag*, *Technews* and *Webmag* (Figure 1 shows one example consent statement; screenshots of all consent statements can be found in Appendix C). Aesthetic manipulation was represented by a blue coloured "Agree" button on the websites *Megazine*, *Techmag*, *Viral* and *Webmag*. Obstruction was represented by the option "Manage options" instead of "Do Not Agree" on the websites *Motivemag*, *Technews*, *Viral* and *Webmag*. Only after selecting "Manage options" was it possible to choose "Do Not Agree". The consent statement of the website *Avision* represented the baseline condition with none of the three design nudges included.

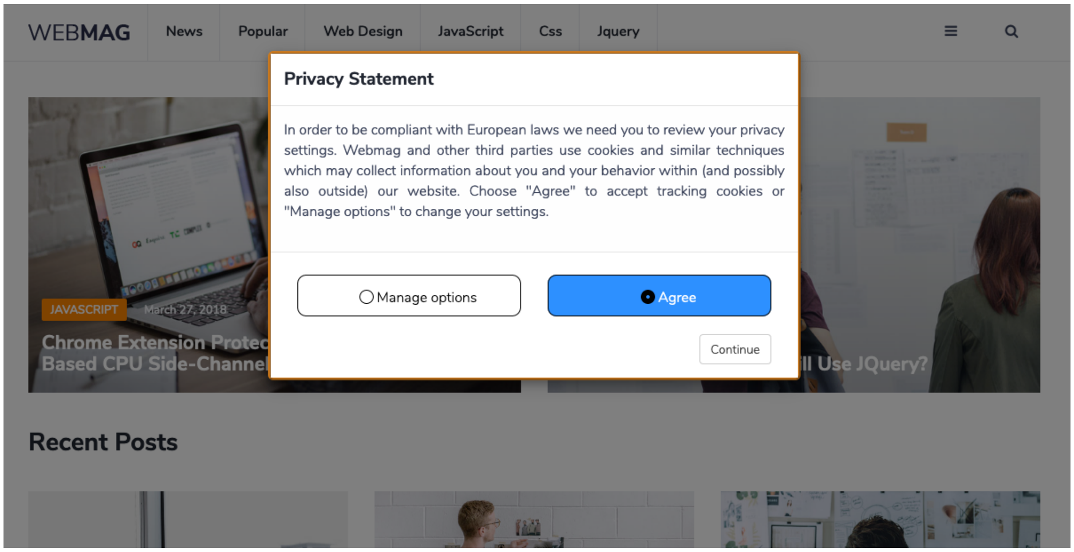

Figure 1. Example consent statement featuring all three dark patterns default, aesthetic manipulation and obstruction. Website: Webmag

Measures. For each consent statement, we assessed a participant's level of perceived control, level of deliberation and several control questions regarding his/her attentiveness during the decision process. Further, we asked participants to report on their general privacy concerns and personal browser setup.

To measure how much control participants felt each consent statement gave them over their personal information we built on the work from Xu (2007). The formulation of the items was adjusted to fit the purpose of the study (see Table 1). Participants could indicate their perceived level of control over their personal data on a slider ranging from “Not at all” to “Complete” (higher values indicate more perceived control). The average of all five items was used as the final outcome variable perceived control in the statistical analysis (range: 0 - 100, M = 31.80, SD = 28.54). Further, the perceived control measure showed very good internal consistency with a raw Cronbach's $\alpha = 0.99$ (none of the individual items increased the overall α if being dropped).

How much participants deliberated about their decision was assessed by the question “How much did you think about your decision before clicking on one option?” (formulation of the item was adapted for the present study; Dijksterhuis, Bos, Nordgren, & van Baaren, 2006). The level of deliberation could be indicated on a slider ranging from “Not at all” to “A great deal” (range: 0 - 100, M = 20.99, SD = 25.33). Lastly the Global Information Privacy Concern scale from Malhotra et al. (2004) was used to assess individual privacy concerns (on a seven-point scale ranging from “Strongly disagree” to “Strongly agree”, range:

1 - 7, M = 4.13, SD = 1.24). For statistical analysis we used the average score of the three items, which formed the scale. The measure individual privacy concerns showed good internal consistency with a raw Cronbach's $\alpha = 0.79$ (again none of the individual items increased the overall α if being dropped).

Several manipulation checks as well as control questions were included to get a better understanding of the participants' behaviour during the study. When reviewing each consent form (in the form of a screenshot) it was asked whether the participant had read the consent information ("Read it completely", "Skimmed it", "Did not read it at all") before clicking on one option as well as whether they remembered which option they had chosen ("Agree", "Do Not Agree"). Further, participants provided information on whether they had installed a browser plugin, which handles/deletes cookies ("Yes", "No"), whether all websites had been displayed correctly ("Yes, all of them", "No, not all of them") and on which device they completed the study ("PC", "Tablet,"Phone"; only Laptop/PC was allowed).

Table 1

Perceived control questionnaire items.

Number	Question
1	How much control did you feel the consent form gave you over the amount of your personal information collected by the company?
2	How much control did you feel the consent form gave you over who can get access to your personal information?
3	How much control did you feel the consent form gave you over your personal information that has been released?
4	How much control did you feel the consent form gave you over how your personal information is being used by the company?
5	Overall, how much did the consent form made you feel in control over your personal information provided to the company?

Note. $M = 31.80$, $SD = 28.54$, Range: 0 - 100, Cronbach's $\alpha = 0.99$ (raw)

Participants

We recruited a total of $N = 228$ participants via the crowdsourcing platform Prolific Academic. The sample size was determined by running a power calculation via simulation using the R package simr (Green & MacLeod, 2016) as well as using the software GPower (Faul, Erdfelder, Buchner, & Lang, 2009) as a fall back strategy to determine the minimum number of participants in case our simulation does not yield a clear estimation (GPower: normal linear regression, $f^2 = 0.15$, power = 0.80, resulted in 103 participants). The simulation was based on pilot data (n=38), following the safeguard power analysis concept of Perugini, Gallucci, and Costantini (2014), we assumed 80% of each obtained fixed effect as a conservative effect size estimator (given that most pilot studies are underpowered; Lakens & Albers, 2017; Vasishth, Mertzen, Jäger, & Gelman, 2018). To achieve a power of 80% (for the smallest observed effect), more than our maximum number of 215 participants (given available resources) was required. Therefore, we aimed for the highest number of participants we could recruit (while taking the GPower calculation as a lower boundary into account), which resulted in N = 228 participants[1].

Inclusion criteria for study participation were an age between 18 and 65 years (to represent a broad range of society) and a current living location in the United Kingdom (to minimise noise in the data because of cultural differences we restricted the study to the biggest participant pool within Prolific Academic). Participants were compensated with 1.70GBP for the successful completion of the study, which was estimated to take around 12 minutes (8.50GBP/h). On average it took participants 9.79 minutes (SD = 4.02) to complete the study. 33 participants were left out of this calculation since they showed very long completion times indicating that they divided the study over several days. Yet, their consent behaviour did not seem to differ from the rest of the sample and thus they were kept for analysis. Additionally, only 5 participants were found to have completed the experiment in less than 5 minutes, which, given the low number, led us to the decision to keep them in the sample as well. Participants who could not finish the study due to technical problems were excluded.

The total sample population consisted of 137 females (60.09%), 91 males (39.91%) and had a mean age of 36.02 years (SD = 11.62). Neither did participants' consent behaviour differ significantly between females (clicked "Agree" in 93.14% of the cases) and males (clicked "Agree" in 94.77% of the cases), $\chi^2(1) = 1.84$, $p = .17$, nor as a function of age, $F(1,1638) = 2.75$, $p = .10$. Similarly, participants perceived control levels did not differ significantly between females (M = 31.29, SD = 28.96) and males (M = 32.46, SD = 28.02), $t(1486.1) = -0.80$, $p = .42$, nor were significantly correlated with age, $r(1547) = 1.24$, $p = .22$. Of all 228 participants who took part in the experiment, 35 dropped out in the second part of the study (i.e., after reviewing the eight news websites). Because

[1] The number of recruited participants is higher than the maximum number we could afford (given available resources) because some participants dropped out during the study. Hence, some of the drop outs were not paid but still kept in the data frame to avoid biased results due to improper handling of missingness.

none of the dropouts happened during the completion of a questionnaire (only in between) and no prevalent pattern of missingness was detected (e.g., the consent behaviour did not differ between participants with complete cases and those who would drop out later on) all subjects' data were found eligible for analysis.

Data Analyses

In line with our preregistration, a mixed-effects models approach was used for the analyses. Jaeger (2008) demonstrated that especially for categorical data with a repeated measures structure, this approach is most suitable. For each of the two dependent variables (consent decision and level of perceived control) separate models with a maximal random-effects structure were fit, following the advice of Barr, Levy, Scheepers, and Tily (2013). Thus, each main model included a per-participant random adjustment to the fixed intercept as well as a per-participant random adjustment to the slope of each within-subject variable (default, aesthetic manipulation and obstruction). Further, main models included individual privacy concerns as a control variable.

Exploratory models were fit adding deliberation as a moderator to the aforementioned design of the main models. Specifically, deliberation was present as a fixed effect as well as part of an interaction with each of the three main predictor variables. Additionally, exploratory models added a per-participant random adjustment to the slope of each interaction term. The distinction between main and exploratory models was, apart from conceptual reasons mentioned in the introduction, needed to ensure that the main models were statistically identifiable (i.e., not too complex given the data) and sufficiently powered. Whereas the main models consisted of 15 model parameters (5 fixed effects, 10 random effects), exploratory models consisted of 45 model parameters (9 fixed effects, 36 random effects), making them only identifiable after reducing the random-effects structures (i.e., reducing model complexity by dropping all random correlations). To determine p values, we computed Type 3 bootstrapped Likelihood Ratio Tests (using 1000 simulations).

Additionally, we calculated descriptive statistics and performed simple group comparisons on all control questions in order to improve our understanding of the participants' decision process.

Results

Main analyses

Regarding consent behaviour we observed that in the majority of cases (93.84%) people chose to agree to the consent statements. Moreover, most people did not vary their consent behaviour between conditions (see Figure 2) but always chose the same option (only 3.95% of all participants changed their consent behaviour between conditions). Consequently, we did not find support for our hypotheses H1a, H1b and H1c, meaning that there was no significant effect of default, Estimate = 0.48(0.36), PBtest = 1.87, p = .20, aesthetic manipulation, Estimate = 0.48(0.36), PBtest = 1.87, p = .22, or obstruction, Estimate = 0.72(0.37), PBtest = 4.12, p = .06, on the outcome consent decision. However, it can be noted that the effect of obstruction was marginally significant, displaying a positive effect value, which is in line with hypothesis H1c (see Figure 3).

Due to convergence problems, we had to drop all random slopes of the model, resulting in a random-intercept-only model. However, given the little within-subjects variability in consent behaviour, the random-intercept might be most predictive of one's consent behaviour (e.g., people who agreed to the consent statement of the first presented news website were most likely to agree to all following consent statements).

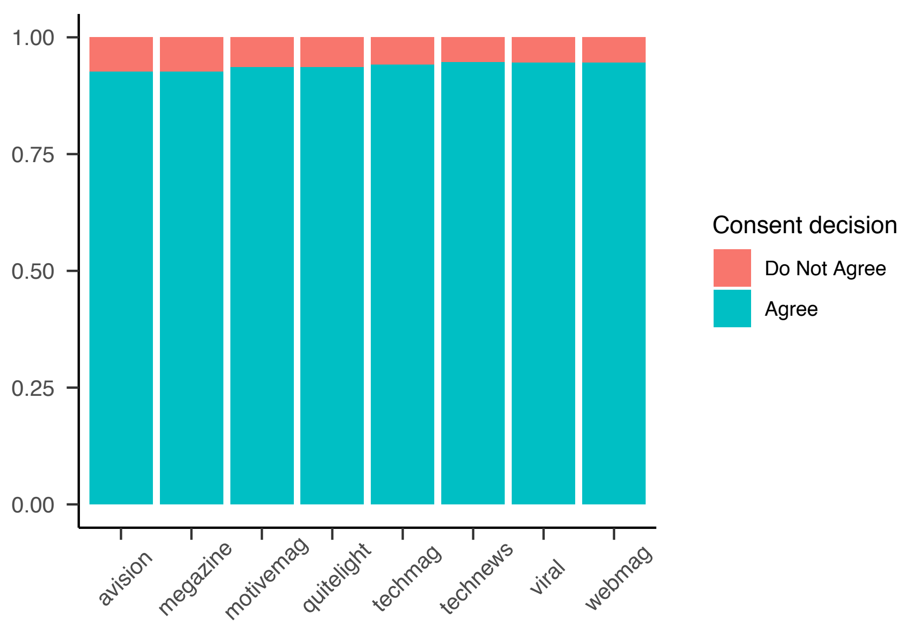

Figure 2. Consent decisions (proportional) by condition (different news websites).

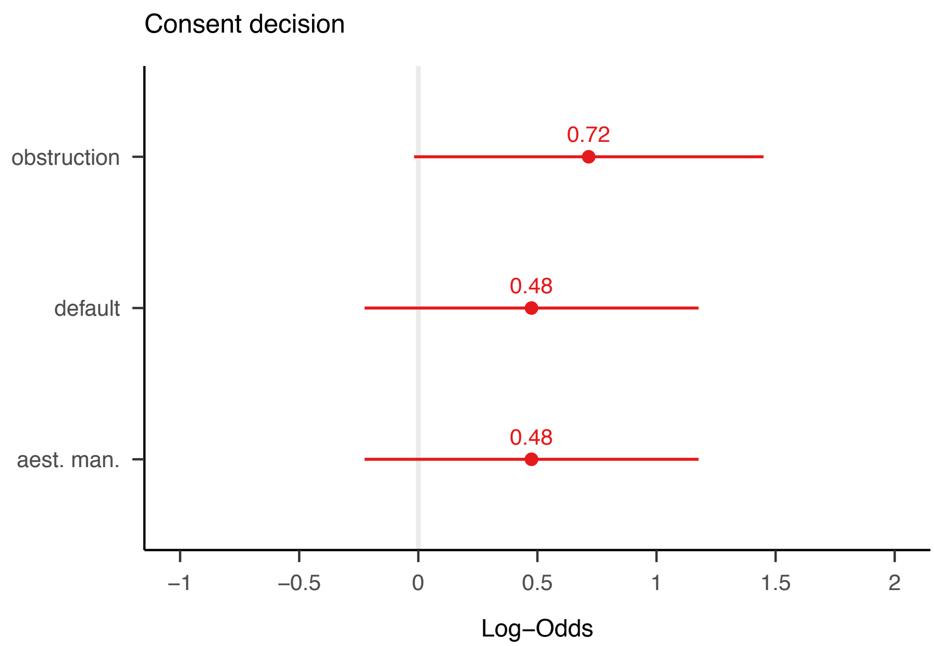

Figure 3. Fixed effect estimates and 95% confidence intervals for the predictors default, aesthetic manipulation and obstruction (outcome consent decision).

Regarding our second outcome variable, perceived control, we found that the main effect of obstruction was significant, Estimate = 1.73(0.48), PBtest = 12.32, p = .003, to our surprise however, displaying a positive effect value, which is associated with an increase rather than a decrease of perceived control (see Figure 4). Hence, hypothesis H2c was not supported. Further, we did not find support for hypotheses H2a and H2b concerning the effects of default, Estimate = 0.10(0.22), PBtest = 0.23, p = .77, and aesthetic manipulation, Estimate = 0.08(0.24), PBtest = 0.12, p = .89. It has to be noted that model diagnostics identified 1.42% of the residuals as multivariate outliers. Accordingly, the model was run with and without multivariate outliers, revealing slight differences in the results. When multivariate outliers were excluded, the effect of obstruction was only marginally significant, Estimate = 1.61(0.48), PBtest = 6.45, p = .06, while there was no change in the results of the other two main predictors default, Estimate = 0.16(0.18), PBtest = 0.82, p = .49, and aesthetic manipulation, Estimate = 0.09(0.18), PBtest = -4.31, p = 1.00. Overall, obstruction seemed to have an effect on perceived control, which cannot be ignored, yet replication is needed to confirm the direction of this effect.

Prior to this analysis, model diagnostics indicated a floor effect of the model residuals, meaning that most residuals were clustered on one side of the scale. This was probably partially due to how this variable was measured (i.e., slider's default position being "Not at all”), which may have led people to report generally low levels of perceived control (*M* = 31.80, *SD* = 28.54, raw data visualisation in Figure 5). Several transformations were tried on the outcome perceived control (e.g, square-root and Box Cox) but none led to a significant improvement of the residual distribution, hence we stuck to the original values to run the analysis.

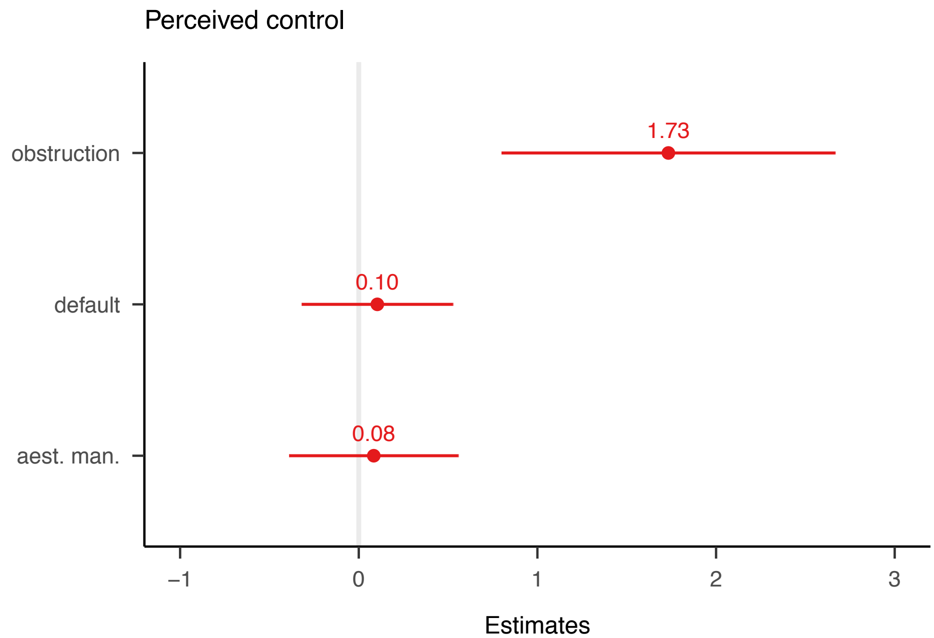

Figure 4. Fixed effect estimates and 95% confidence intervals for the predictors default, aesthetic manipulation and obstruction (outcome perceived control).

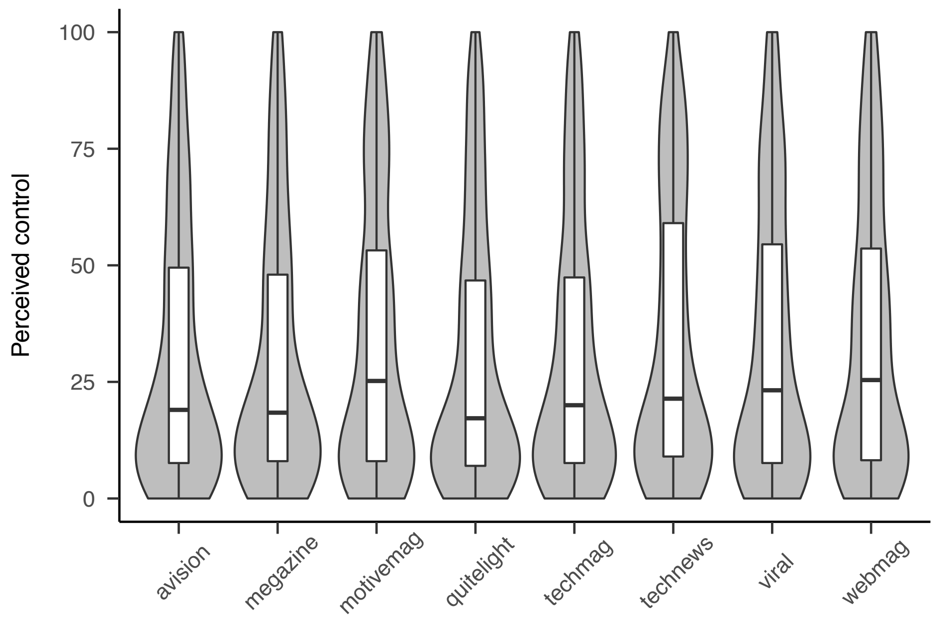

Figure 5. Violin plots showing levels of perceived control by condition (different news websites). Grey shapes visualise the distribution of the variable, white bars represent box plots.

Exploratory analysis

To investigate possible moderation effects of deliberation on the relations between each of the three predictor variables (default, aesthetic manipulation and obstruction) and the outcome variables consent decision and perceived control, we ran two additional mixed-effects models. As in the main analysis, we had to drop all random slopes of the model with consent decision as the outcome variable due to convergence problems, resulting in a random-intercept-only model.

We did not find any support for a significant moderation effect of deliberation on the relations between consent decision and the three predictor variables default, Estimate = 0.14(0.35), PBtest = 0.15, p = .77, aesthetic manipulation, Estimate = -0.17(0.37), PBtest = 0.21, p = .70, and obstruction, Estimate = 0.56(0.47), PBtest = 1.65, p = .27. Neither did we find support for a significant moderation effect of deliberation on the relations between perceived control and the three predictor variables default, Estimate = -0.06(0.21), PBtest = 0.06, p = .97, aesthetic manipulation, Estimate = -0.12(0.24), PBtest = 0.21, p = .86, and obstruction, Estimate = -0.13(0.38), PBtest = 0.12, p = .88. This may be due to the fact that participants reported generally low levels of deliberation as reflected by the raw data, which is visualised in Figure 6. Similar to the perceived control measurement, absolute values of deliberation should be interpreted cautiously due to the assessment procedure (i.e., slider's default position being "Not at all").

However, in the latter model with perceived control as the outcome variable, the main effect of obstruction was significant, Estimate = 1.74(0.46), PBtest = 14.00, p = .001, as well as the main effect of deliberation, Estimate = 5.49(0.78), PBtest = 44.34, p = .001. As model diagnostics detected 1.49% of multivariate outliers the model was run with and without them but the pattern of results did not differ. The significant effect of obstruction was in line with the result from the main analyses, which already identified obstruction as a significant predictor of perceived control, however, the direction of the effect was again contrary to what we hypothesised. The positive, significant main effect of deliberation suggests that the more participants deliberated before making a choice, the more control they perceived over their personal data. However, considering Figure 7, the broad spread of data points, especially towards the higher values, makes further investigation inevitable before claiming a causal link.

Overall, it has to be noted that due to high model complexity given our data (as explained in the method - data analyses section), interpretation of these exploratory findings should be done with caution, also given the assessment of perceived control and deliberation through self reports. Nevertheless, obstruction emerged repeatedly as the design nudge with the biggest effect estimate of all three tested dark patterns, which will be discussed later on.

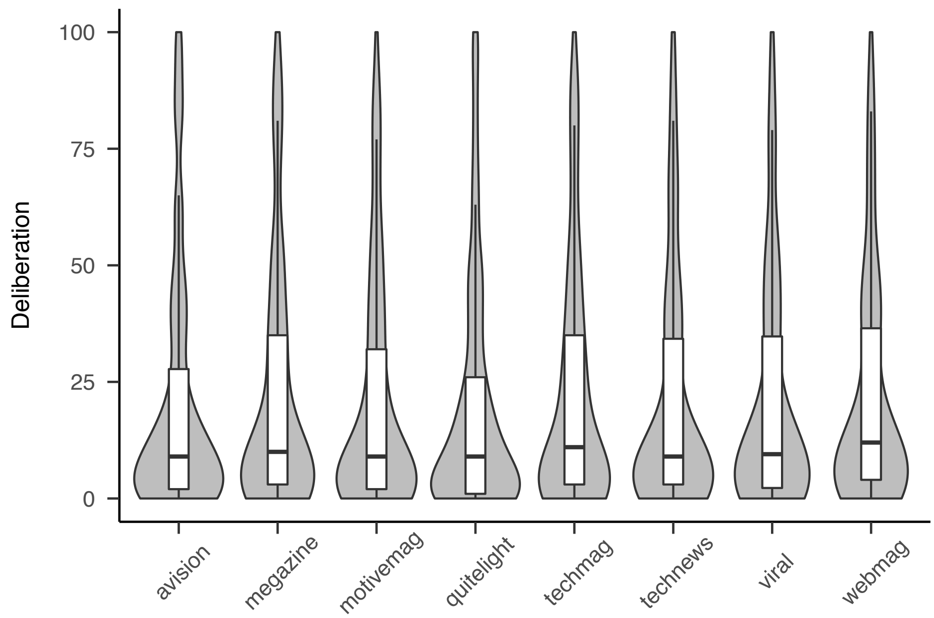

Figure 6. Violin plots showing levels of deliberation by condition (different news websites). Grey shapes visualise the distribution of the variable, white bars represent box plots.

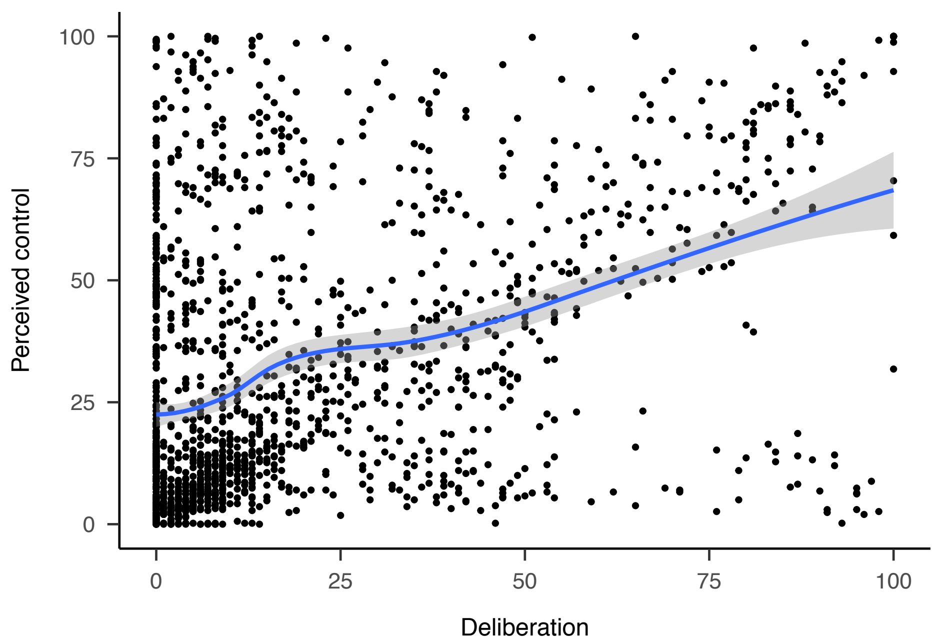

Figure 7. Relation between levels of deliberation and perceived control (regression method LOESS).

Control Questions

To get a better understanding of the participants' behaviour during the study several manipulation check and control questions were asked. To the question whether they had read the consent information before clicking on one option, participants responded in only 10.06% of the cases that they had read the information completely. In 49.61% of the cases people stated to have skimmed the information while in 40.32% of the cases they reported to not have read the information at all, meaning that roughly 90% of all presented consent statements were not properly read.

Further, it was asked whether participants could remember their consent decisions and only in 1.29% of the cases people reported that they could not remember. Comparing each given answer with the actual decision revealed another 1.29% of incorrectly remembered decisions, resulting in total to 2.58% of all decisions, which could not be remembered. This means that participants were generally able to remember their consent decisions but probably also because they always chose the same option.

Additionally, 31.09% of all participants (with complete cases) stated to have a browser plugin installed, which handles or deletes cookies. The consent behaviour did not significantly differ between those participants with a plugin and those without, $\chi^2(1) = 3.18$, $p = .07$. Equally, we did not observe significant differences in the levels of perceived control between those with a plugin ($M = 30.70$, $SD = 27.11$) and those without ($M = 32.36$, $SD = 29.21$), $t(989.82) = 1.08$, $p = .28$.

Overall, it can be noted that although most participants reported to not have properly read the consent information, they remembered their choice. Further, individual browser setup did not seem to influence how people perceived and acted on the consent statements regarding web tracking. How these findings relate to the results of the main analyses will be discussed in the following section.

Discussion

The goal of this project was to investigate whether design nudges (i.e., dark patterns) in consent statements lead users to choose the privacy-unfriendly option more often than the privacy-friendly one, and whether they deprive users from their perceived control over their personal data. Although we could show that the majority of participants chose always the privacy-unfriendly option and reported a lack of control over their personal data, we did not find clear support for that being due to the design nudges. Obstruction was the only design nudge, which appeared to have some effect on our outcome measures. In light of the consent decision, obstructing the "Do Not Agree" option seemed to have a greater impact on which option participants choose than preselecting the “Agree” option or making the “Agree” option more salient through colouring. Unexpectedly, we found that obstruction led people to perceive more rather than less control over their personal data. This effect, however, might be a result of the generally low levels of perceived control, which we observed across all conditions (as shown in Figure 5), making relative differences less meaningful.

Apart from specific effect structures the data provided substantial ground for further insights into how people perceive consent statements as well as how they act on them. Most participants reported that they did not read the consent statements properly and did not think much about their decision before choosing one option. Still the majority of participants agreed to all consent statements in a seemingly default manner. This clearly shows that the current notice and choice model does not work as intended (also under the GDPR), and that people do not seem to engage with privacy decisions in a rational and deliberate manner, as assumed by the privacy-calculus theory and GDPR.

Explanatory approaches

We argue that there are 4 possible explanations for the observed default behaviour. First, as people were paid a fixed amount of money for study participation, they might have had some interest in finishing the study as quickly as possible, resulting in time pressure as a possibly confounding factor. However, time constraints apply not only to this research context but also to everyday life where people have other goals in mind than reviewing consent statements. Second, despite the preliminary pilot we conducted to test the credibility of our cover story, we cannot completely rule out that some participants clicked on “Agree” because they perceived everything as part of a “trustworthy” research study.

Third, another explanation provides the so-called Fitts’s law, which is a predictive model of human movement stating that it is easier and faster to hit larger targets closer to you than smaller targets further away from you (MacKenzie, 1992). In our design of the consent statements the “Agree” option was on the right-hand side and thus closer to the “Continue” button (which was also on the right-hand side) than the “Do Not Agree” option, which was on the left-hand side (see Appendix C). This setup was inspired by what is most used in real-life practice but might have acted as an additional design nudge, which should be investigated by future research. Nevertheless, Fitts’s law cannot explain why most of those participants who chose “Do Not Agree” also seemed to be in a default mode by always choosing the same option.

Fourth, people might have shown the consent behaviour in our study, which they are conditioned to from everyday life. Many web services do not even provide the opportunity to choose between different options but make tracking cookies obligatory for the use of their services (called "forced action" by Gray et al., 2018). Hence, people often have to consent to the policy in order to reach their goal (i.e., accessing the content of the web service). It might be that the conditioned behaviour from reviewing consent statements on a daily basis overwrote the effects of our design nudges in the study. This would be in line with the finding that people did not think much about their decision but seemed to follow the heuristic approach of choosing the option they normally choose. Additionally, this is further evidence against the privacy-calculus theory given that people did not show rational decision behaviour even in the clear circumstances of our study. It has to be emphasised that the majority of real-life consent statements does not offer a clear cost and benefit tradeoff resulting in a decision under uncertainty for the user. As laid out by Acquisti et al. (2017), especially decisions under uncertainty where possible outcomes are unknown (i.e., bounded rationality) lead users to the application of heuristics.

The ambiguity, which is normally present in real-life consent statements, might also explain why participants generally reported low levels of perceived control over the decision concerning their personal data. Although participants had (theoretically) full control over each decision in our study (i.e., for each consent statement there was the possibility to choose "Do Not Agree") they did not seem to perceive it that way, possibly because they are conditioned to ambiguous real-life consent statements, which do not always offer a "real" choice. Similar as for the observed consent behaviour it might be that people are conditioned to consent statements, which do not offer much control (often because of a lack of choice), which covered any effects of the design nudges. This general lack of perceived control is exemplified by the finding that participants who had a browser plugin installed, which aims at increasing control over web tracking, did not perceive to have more control over their personal data than those participants without a plugin. Nevertheless, it has to be taken into account that the assessment of perceived control levels happened with a time delay to the actual consent decisions (i.e., after all eight news websites had been reviewed). This was due to our study design involving the cover story about the first impression of the design of news websites, which would have been compromised when drawing attention on the consent statements during part 1 of the study (i.e., while reviewing the news websites).

Implications

Taking these findings into account the question arises how problems of the current notice and choice model can be addressed. We believe that there are two ways to tackle the issue: Target the user versus target consent practices. By targeting the user we mean any attempt to change the behaviour or competences of the user. We base ourselves on Hertwig and Grüne-Yanoff (2017) to differentiate between nudging approaches, which try to change behaviour by altering the choice architecture, and boosting approaches, which focus on competence building to enable certain behaviour. Using classic, non-educative nudges to change the observed default behaviour in consent statement situations would mean to nudge "in the other direction" (i.e., towards the privacy-friendly option). Standing in contrast to dark patterns we title such privacy-friendly nudges "bright patterns". Bright patterns do not require any motivation from the user but may lead to similar problems as their dark counterparts, namely unreflected default behaviour as well as users' perception of a lack of control (not to mention practical feasibility, which will be discussed later).

Further, there are educative-nudges (after Sunstein, 2016b) such as reminders or warnings, which build a middle ground between nudging and boosting because they require some level of motivation to foster a context specific competence (called short-term boosts by Hertwig & Grüne-Yanoff, 2017). In the context of consent statements, this could mean feedback about possible consequences of the decision when users want to make a choice. Because this feedback would need to be implemented by the company or institution asking for consent practical feasibility remains questionable.

Lastly, there are long-term boosts, which aim at a permanent change of skills and decision tools. In our case boosts, which aim at building procedural rules such as "When I see a consent statement I read the provided information before making a choice" could be suitable to break out of the automatic default behaviour and to form the competence of actively deliberating before making a choice. However, long-term boosts are often more costly than nudges (e.g., changing a default requires less time and effort than creating an intervention to form procedural rules) and essentially necessitate peoples' motivation to acquire new skills.

In light of consent statements, it can be assumed that peoples' motivation to deliberate about them is rather low, given that in most cases they represent hurdles to ones' actual goals (e.g., reading articles on a news website). If individuals lack the motivation to build certain competences, Hertwig (2017) advises to use nudging rather than boosting approaches. This brings us back to bright patterns, which do not require motivation from the user but, apart from the problems mentioned earlier, seem unrealistic in their actual application, given that the companies using dark patterns usually have an interest in collecting user data. Consequently, user focused approaches seem unrealistic for the context of consent statements.

The second way we propose to tackle the issue is by targeting current consent practices. Our consent statements were designed in a way that they represent a majority of those statements used in practice under GDPR. Thus, the results of our study demonstrate that GDPR did not succeed in changing consent statements in a way that people give consent in an informed and freely given manner, considering that most participants did not read the consent information and reported a lack of control over their personal data. Dark patterns may play a role in that but based on our study findings it cannot be concluded that stricter design regulations for consent statements alone (i.e., banning dark patterns from consent statements) would resolve the problem because the majority of participants also agreed to web tracking in the baseline condition (see Figure C1) without any design nudge present (although future research should investigate the effects of Fitts's law as an additional design nudge).

Another question is: how much do users actually want to deal with reviewing privacy policies and why did the notice and choice model become the standard for privacy self-management, given that the main purpose of it is legal protection for the data processing institution asking for consent? In that, the notice and choice model puts a lot of responsibility on the user by making it possible to easily share personal data in return for incentives such as personalised advertising or other online services. This brings us to the underlying idea of the notice and choice model that privacy is an individual good, which can be traded in an economic sense (e.g., in exchange for personalised advertising). As described by Hull (2015), the notice and choice model not only fails in protecting privacy but also denies the social value of it, meaning that the level of privacy of each individual affects society as a whole. Cohen (2013) points out that privacy is necessary to create a safety net with the space and independence needed for critical thinking in order to engage in reflective citizenship and try out innovative ideas in a protected environment.

Ultimately, stricter regulation of what kind of data processing can be agreed to through consent statements may be necessary to change current practices. Friedman, Howe, and Felten (2002) already warned us in the early days of informed consent online of an overwhelming amount of consent queries, which result in users who become numb to the process of informed consent. Thus, a first goal should be to reduce the number of consent statements an average internet user has to review while browsing the web, making consent statements less prone to conditioned default behaviour. In sum, our results suggest that the current version of the notice and choice model is not suited to capture people's privacy preferences. We cannot conclude that this is solely due to dark patterns, but they may play a role in conditioning the default behaviour we observed.

Limitations and Future Work

To address some of the limitations of our study, future research should investigate what consent behaviour people display when bright patterns are used instead of dark patterns, that is when people are nudged towards the privacy-friendly option. Specifically, the location of the presented options (after Fitts's law) should be taken into account because button placement is likely to act as an additional design nudge, which is, at least to our understanding, not fully captured by what Gray et al. (2018) call "false hierarchy". Possibly interesting in this regard would be the inclusion of eye-tracking measurements to follow participants visual attention while reviewing consent statements.

Furthermore, a compromise between ecological validity and controlled experimental setting had to be made for the design of our consent statements. To include all three dark patterns at the same time, we had to choose a consent statement setup, which deviated slightly from most real-life consent statements. Namely, we presented the available choice possibilities in the form of radio buttons (which can be ticked) instead of clickable buttons because regular buttons cannot be preselected.

Additionally, we had to tweak some aspects of the design of each consent statement (see Appendix C) to match the design of the corresponding news website and make the cover story of eight independent, external news websites plausible. While these changes may seem arbitrary, we paid close attention to not change any parts close to the choice options in which our manipulations where applied. After all it can also be argued that all consent statements still looked very similar and this led people to not deviate between conditions. To circumvent these problems in the future we can imagine that a longitudinal study design may provide the possibility to show identical consent statements to the same participant but with enough time delay to avoid memory effects. A longitudinal study design may also offer to collect more consent decisions per participants and thus facilitate the testing of more complex models, which could incorporate possible interaction effects of different design nudges. Moreover, future research could not only investigate whether people remember if they gave consent or not, which is easy if one always chose the same option, but also whether they remember the content they consented to. Further, it would be interesting to see if peoples' default behaviour is consistent across different online contexts. Lastly, our design complicated the reliable assessment of participants' perceived control over their personal data, which future research should pick up on. We hope to have created a starting point for the development of a perceived control measure specifically for privacy decisions.

Overall, this pioneer project shed light on some of the mechanisms of dark patterns, however, follow up research is needed to disentangle their effects more thoroughly. For this purpose, we discussed possible limitations of our study and gave recommendations for improvement. Further, our research findings demonstrate some of the shortcomings of privacy self-management online, which is currently represented by the notice and choice model. We reflected on possible solutions to face these shortcomings, one of them suggesting that the number of consent statements people are confronted with on a daily basis might have to be reduced in order to avoid the present numbness regarding them. Rethinking under which circumstances consent statements offer meaningful choice (and under which they do not) might be the first step towards a better handling of digital privacy.

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Appendix A
R language and packages

We used R (Version 3.5.2; R Core Team, 2018) and the R-packages *afex* (Version 0.23.0; Singmann, Bolker, Westfall, & Aust, 2019), *BaylorEdPsych* (Version 0.5; Beaujean, 2012), *car* (Version 3.0.2; Fox & Weisberg, 2011), *cowplot* (Version 0.9.4; Wilke, 2019), *DHARMa* (Version 0.2.4; Hartig, 2019), *dplyr* (Version 0.8.1; Wickham et al., 2019), *effects* (Version 4.1.0; Fox & Weisberg, 2018; Fox, 2003; Fox & Hong, 2009), *ggplot2* (Version 3.1.0; Wickham, 2016), *gridExtra* (Version 2.3; Auguie, 2017), *here* (Version 0.1; Müller, 2017), *influence.ME* (Version 0.9.9; Nieuwenhuis, Te Grotenhuis, & Pelzer, 2012), *kableExtra* (Version 1.0.1; Zhu, 2019), *knitr* (Version 1.23; Xie, 2015), *lattice* (Version 0.20.38; Sarkar, 2008), *lme4* (Version 1.1.21; Bates, Mächler, Bolker, & Walker, 2015), *Matrix* (Version 1.2.15; Bates & Maechler, 2018), *mvnmle* (Version 0.1.11.1; Gross & Douglas Bates, 2018), *papaja* (Version 0.1.0.9842; Aust & Barth, 2018), *pastecs* (Version 1.3.21; Grosjean & Ibanez, 2018), *psych* (Version 1.8.12; Revelle, 2018), *rmarkdown* (Version 1.13; Xie, Allaire, & Grolemund, 2018), *scales* (Version 1.0.0; Wickham, 2018), *simr* (Version 1.0.5; Green & MacLeod, 2016), *sjPlot* (Version 2.6.2; Lüdecke, 2018), *tidyr* (Version 0.8.3; Wickham & Henry, 2019), and *VIM* (Version 4.8.0; Kowarik & Templ, 2016) for all analyses and reporting.

Appendix B
Consent information text

Example consent information text from condition 1, news website Avision:

"we need you to review your privacy settings to be compliant with European laws. Avision and other third parties use cookies and similar techniques which may collect information about you and your behavior within (and possibly also outside) our website. Choose 'Agree' or 'Do Not Agree' to accept or refuse tracking cookies."

Appendix C
Consent statements

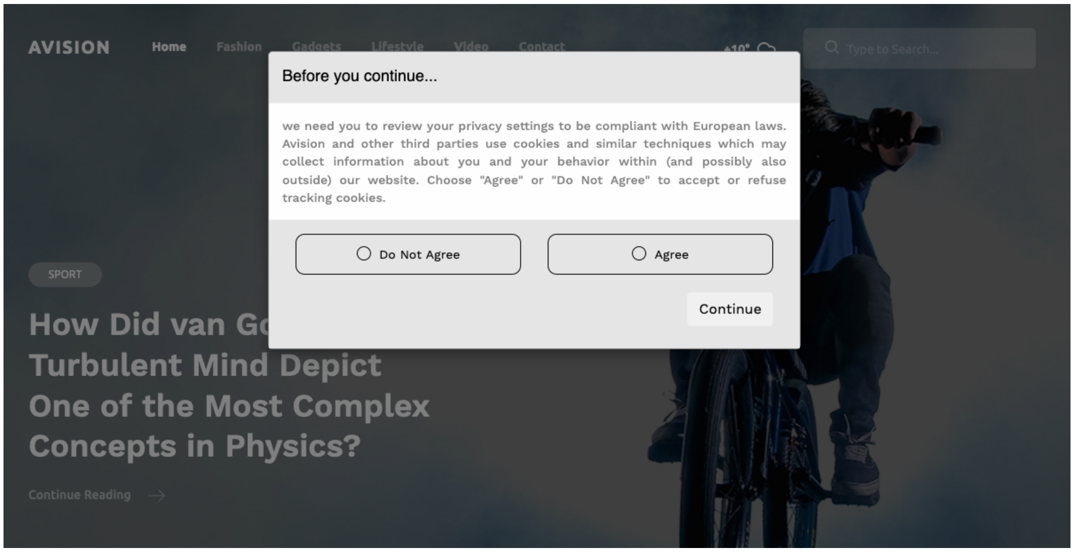

Figure C1. Condition 1. Baseline. Website: Avision

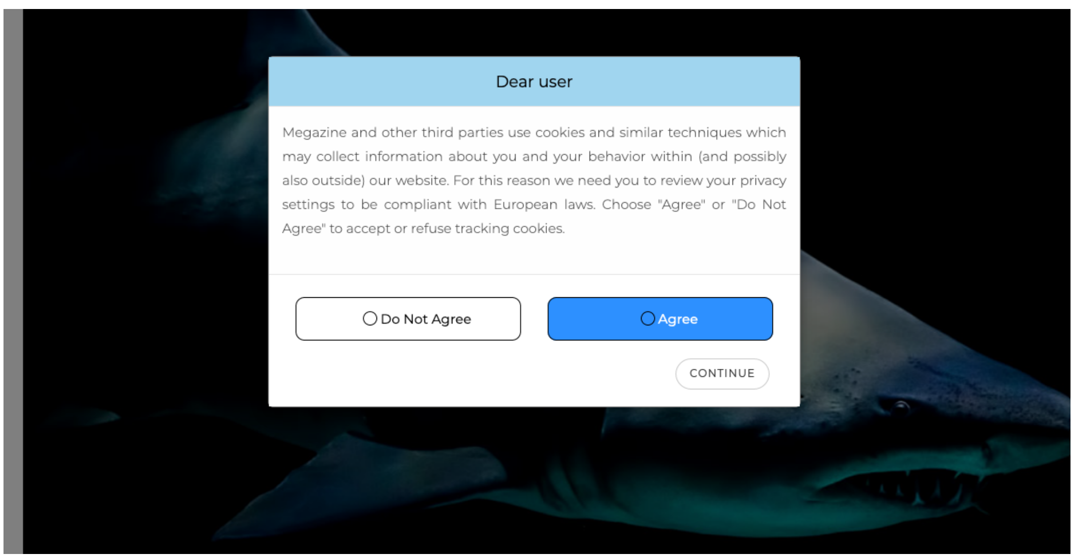

Figure C2. Condition 2. Aesthetic manipulation. Website: Megazine

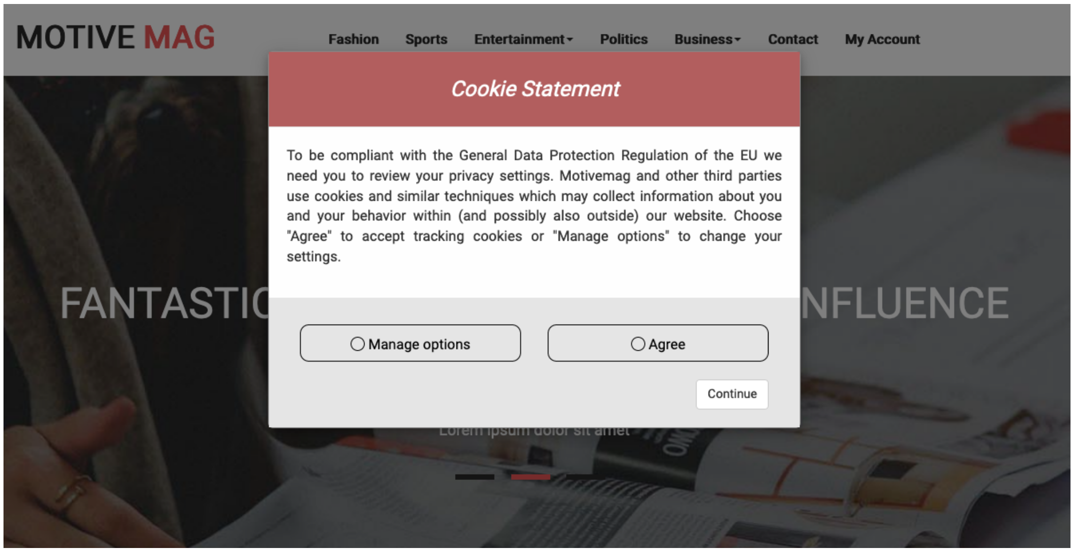

Figure C3. Condition 3. Obstruction. Website: Motivemag

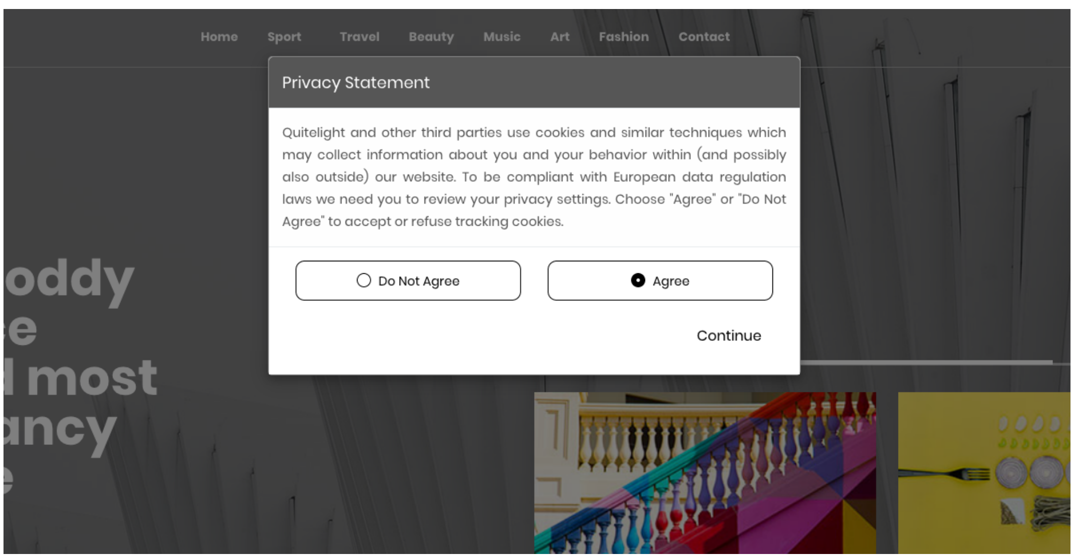

Figure C4. Condition 4. Default. Website: Quitelight

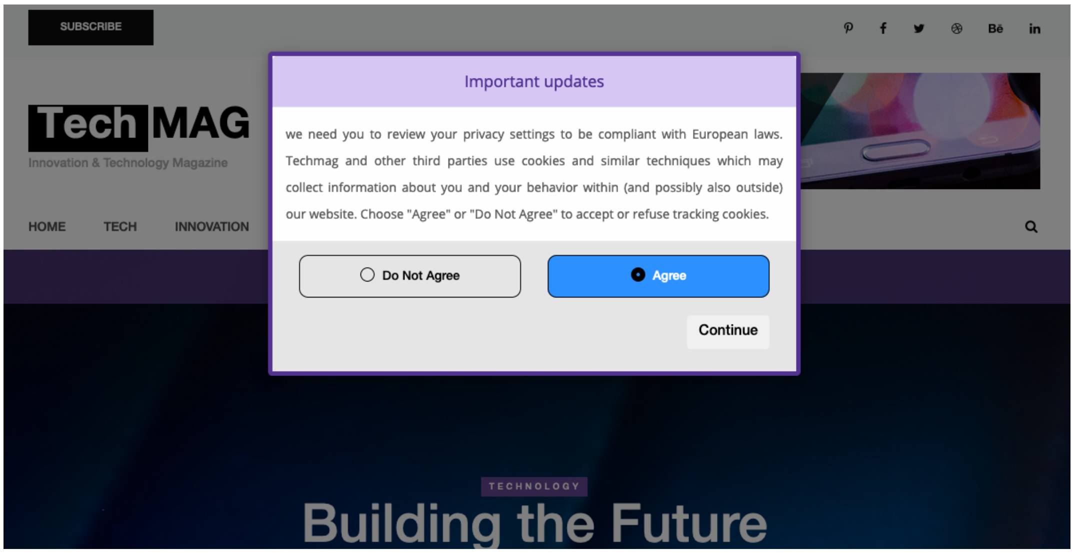

Figure C5. Condition 5. Default and aesthetic manipulation. Website: Techmag

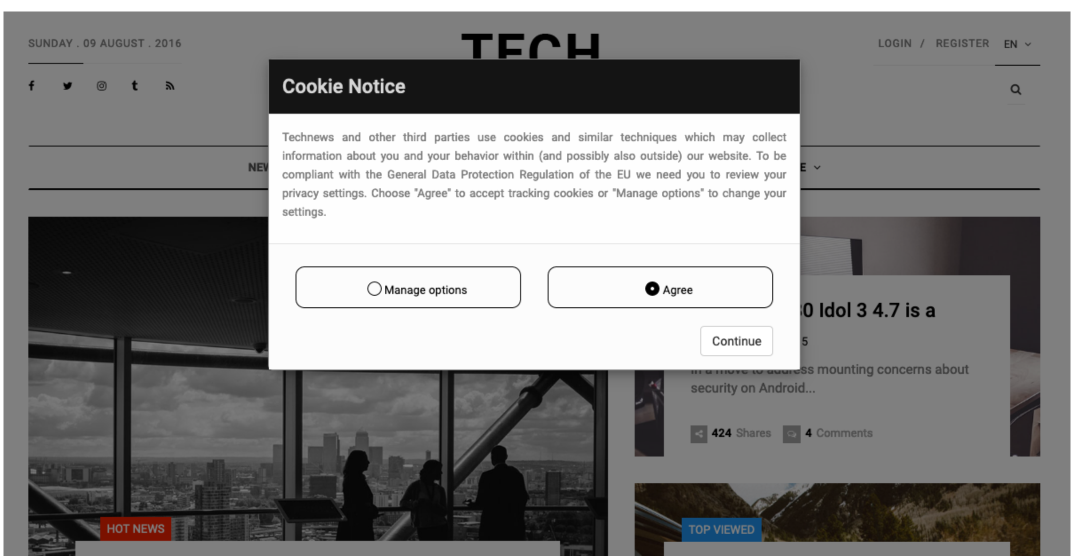

Figure C6. Condition 6. Default and obstruction. Website: Technews

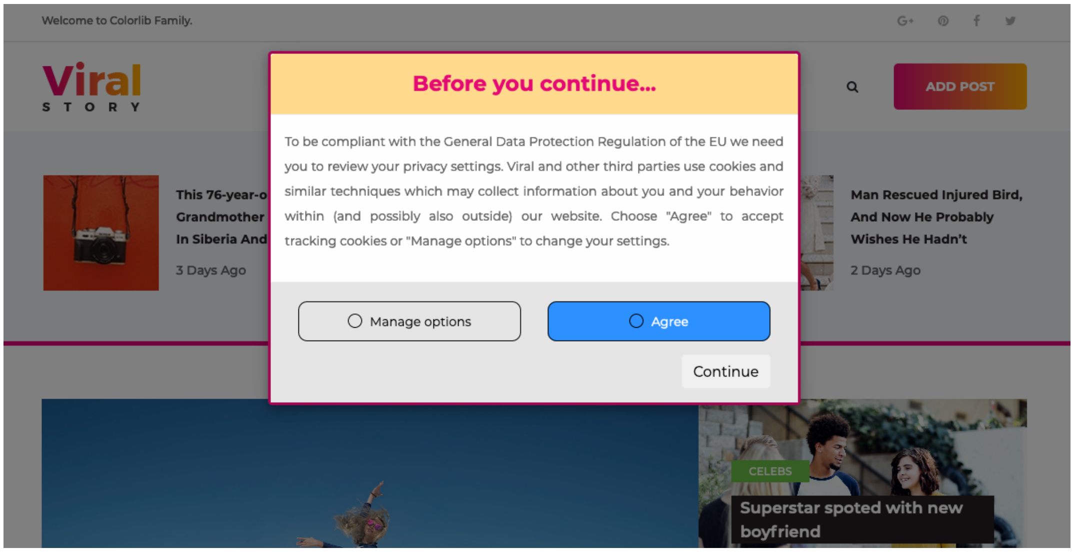

Figure C7. Condition 7. Aesthetic manipulation and obstruction. Website: Viral

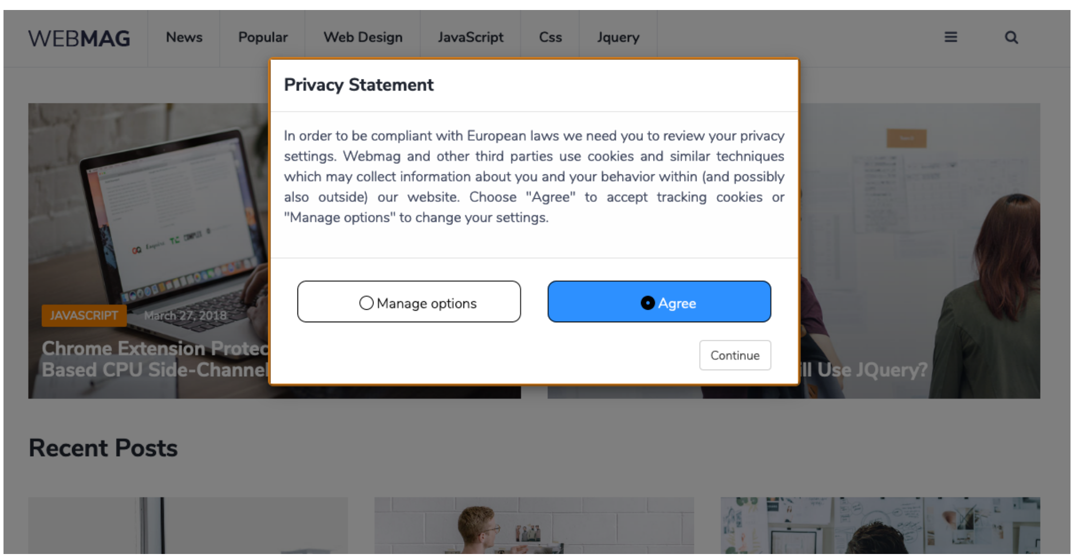

Figure C8. Condition 8. Default, aesthetic manipulation and obstruction. Website: Webmag

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