Reconsidering Privacy Choices: The Impact of Defaults, Reversibility, and Repetition

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Abstract

Despite significant stated privacy concerns among online consumers, research has found almost uniform acceptance of online consent decisions. In recent years, policy makers have adopted sweeping privacy-related regulations to address these concerns. These regulations change the way that online consent is elicited, in hopes of encouraging more deliberative and self-interested privacy decision making by consumers. This study aims to explore the effects of these changes on consumer consent decisions. We isolate three specific tenets of modern privacy regulation, reduction in privacy consent opted-in by default, reversibility, and repeated consent, and explore their effects on individual behavior. We conduct an online experiment that presents participants with actual disclosure decisions that asks participants to link sensitive disclosures to personal information through the decision to "log-in." Expectedly, we find that active choice consent structure and a protective opt-out consent structure decrease log-ins significantly compared to default opt-in. However, opposite the expectation that repeated exposure will lead to less susceptibility to choice defaults, we find that repeated exposure increases the effect of choice defaults, further entrenching their impact. For reversible consent decisions, we also find the surprising result that both explicit reversibility and explicit irreversibility increase the impact of protective defaults by up to 50%. We conclude that while opt-out defaults can drive more protective consumer behavior, in combination with reversibility and repeated exposure, they may the unintended effects of an over-reaction by consumers and lead to drastic reductions in consent provided. Our results extend the current privacy literature and have significant implications for consumers, firms, and policy makers.

1. Introduction

Offering consumers granular privacy choices online promises protections for consumers who desire it while allowing innovation for firms reliant on consumer personal information. Legal scholars and policy makers however, argue that the potential value of granular privacy choices as a mechanism of consumer protection has not been realized (Solove 2013). In online settings with well documented consumer privacy concerns, permissions from consumers are often astronomically high and this consent elicitation is often never revisited. For example, research on the AdChoices program (which gives users the ability to opt-out of behaviorally targeted ads), shows that the program was used in only 0.23% of all American ad impressions (Johnson et al. 2020). Some scholars interpret high levels of consent as consumer indifference to privacy concerns or the high valuation they place on the digital services provided (or both) (Luohan Academy 2021). Policy makers disagree that consumers choices online reflect an active evaluation of the benefits and costs of data sharing. Rather, they point to implicit and difficult to reverse permissions garnered through convoluted privacy policies and privacy choices buried in complex menus that require consumers to actively unselect options to opt-out (FTC 2013). Research substantiates this premise and finds that individuals overwhelmingly agree to privacy policies even when they include naming rights for their first child, access to the airspace above their homes for drone traffic, and sharing all of their data with the National Security Agency (Obar and Oeldorf-Hirsch 2018).

Recent changes to global privacy regulation reflect policy makers' concerns with the status quo for privacy choice online. The General Data Protection Regulation (GDPR) became law in Europe in 2018[1] and requires, among other things, that permission for collections and use of personal information be solicited in an active manner and not through implicit data allowances, disallows the use of opt-in defaults for most privacy consents, and requires that permissions are easily reversible and are revisited periodically through consent re-elicitation. The California Privacy Rights Act (CPRA) amended pre-existing California law soon after[2] and instituted similar requirements to GDPR. Importantly, the extant privacy literature only partially informs the impact of such drastic and widely applicable changes to online consumer privacy choices.

With respect to changes to choice defaults, recent work substantiates the powerful role cognitive biases and "choice architecture" (e.g. choice defaults) play in privacy choice settings (Acquisti et al. 2017; Adjerid et al. 2019; Egelman et al. 2013; Keller et al. 2011; Thaler and Sunstein 2008; Thaler et al. 2013). Thus, policy decisions to prohibit permissive defaults and institute active choices or protective defaults are likely to substantially alter consumer privacy choices online. What is less clear from the privacy literature is the impact of policy attempts to convert online privacy choices from one-off, relatively permanent choices to dynamic choices which are re-visited by consumers and easily reversible. The re-visitation and reversibility of privacy choices can have intriguing effects on privacy decisions. For example, Peer et al. 2016 (the only work we are aware of evaluating reversibility in privacy settings) find that providing reversible privacy choices has the counter-intuitive effect of decreasing disclosure (despite objectively reducing the risk of disclosure). More so, reversibility and revisitation of privacy choices are likely to have important intersections with the impact of cognitive biases and choice

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[1]Regulation (EU) 2016/679 https://gdpr-info.eu/
[2] https://www.manatt.com/insights/newsletters/client-alert/the-california-privacy-rights-act-has-passed

architecture online (e.g. choice defaults). For instance, literature in economics is divided on the effect of experience on the impact of cognitive biases in decision making. Some present evidence that individuals can learn to overcome decision biases with experience (Sellier et al. 2019; Smith 1976; Smith 1982). Others show that habituation and fatigue can lead to additional biases, further hindering decision making (Schaub et al. 2015).

Given the significance and scope of policy changes around consumer consent and the limited research informing their impact on consumer behavior, our research aims are to 1) evaluate the effect of changing choice architecture on consumer privacy choices and 2) explore how reversibility and repeated exposure impact decision making across different manipulations of choice architectures.

We conduct a two factor (3x3) between-subjects online experiment with participants recruited through Prolific[3]. Participants first create a research profile which asks for demographic information (similar to a profile page for a web service) and a social desirability assessment (Crowne and Marlowe 1960)[4]. Each participant then takes three separate studies that ask for sensitive disclosures related to sexual behavior, romantic involvement, or criminal history. Participants are informed that, if they log-in to their research profile, the demographic data in their research profile will be associated with their responses. They are also informed that their profile would be used to track their responses across multiple studies, and that consenting would allow for customized research requests in the future based on their responses.[5] Otherwise, their

[3] Prolific is an online subject recruitment platform designed specifically for researchers. It has been shown to provide data quality comparable to other platforms while providing participants that are more naïve to "common experimental research tasks" (Peer et al. 2017).
[4] We introduced a social desirability assessment because default effects are often a function of one's desire to adhere to a socially optimal choice.
[5] It is against the terms of service for most online research platforms (e.g. Prolific, Amazon Mechanical Turk) to ask directly identifying information from participants (e.g. email address, name).

answers would be disconnected from the research profile and no additional opportunities would be available. Participants are randomly assigned to one of nine conditions that manipulate two experimental factors. The first factor, choice architecture, alters whether the option log-in choice is selected by default (baseline condition), an active choice decision (i.e. no default selected), and a protective default where the option to be anonymous is selected by default. The second dimension is whether the participant decision is explicitly reversible, the decision is explicitly irreversible, or the participant is given no information about the reversibility of their choice. These conditions are held constant across the three studies. These experimental manipulations allow us to evaluate the impact of choice architecture and reversibility while the repeated nature of the task allows us to evaluate the impact of multiple exposures to the privacy choice.

In terms of the first research objective, we find large and significant effects of changing choice architecture. Those in the default opt-in condition (our control group), the active choice condition, and the default opt-out condition logged in approximately 92%, 81%, and 51% of the time, respectively. This shows the effectiveness of an active choice while highlighting the strength of a more protective opt-out default.

Our second research objective considers the intersection of changing choice architecture with reversibility in a choice context. Our first major finding shows the surprising result that when combined with a protective opt-out default, both reversibility and irreversibility negatively affect log-in rates. For those in the protective opt-out condition, log-in rates when the decision was made explicitly reversible, explicitly irreversible, or neither reversible nor irreversible were 47%, 46%, and 56% respectively. Given that these two seemingly opposite constructs affect our outcomes in the same direction, we speculate that both reversibility and irreversibility signal to the user that the decision introduces privacy concerns, leading to more protective behavior.

Next, we consider the role of repeated exposure on the effects of choice architecture. Without a reversibility statement, both defaults get stronger over time in their respective directions. The log-in rates *increase* by ~2% after each exposure to the privacy choice when presented as a default opt-in while log-in rates *decrease* by ~4% after each exposure to the privacy choice when presented as a protective opt-out default. This result shows that repeated exposure is unlikely to attenuate the effect of decision biases. However, we find that making a choice reversible or irreversible counteracts the increase in decision biases for those in the default opt-in condition. In other words, without any explicit reversibility, the effect of the opt-in default grows over time (as stated above). When, instead, reversibility or irreversibility is introduced, the effect of the default remains the same over time, instead of increasing. Our interpretation of this result is that the potential of either reversibility or irreversibility to prime privacy concerns counter-acts the potential of individuals to be more susceptible to permissive defaults over time. Comparatively, when reversibility is introduced to those in the protective opt-out condition, consent is driven down even further, likely creating ceiling effects. Therefore, those prone to be impacted by the default exhibit this behavior at the first exposure to the choice, with the effect persisting, but not growing, over time.

Our findings contribute to several streams of research. First, we contribute to the stream of research within the privacy decision making literature highlighting the importance of behavioral biases in decision making (Acquisti and Grossklags 2005; Acquisti et al. 2012; Li et al. 2008; Tsai et al. 2011).

Specifically, we reaffirm the influence that default choices have on individuals' privacy related behavior (Gross and Acquisti 2005; Johnson and Goldstein 2003; McKenzie et al. 2006). In addition, past work has primarily focused on one-off choices (Acquisti and Grossklags 2005), when in reality most modern privacy choices are repetitive. Thus, we extend work on the influence of biases in privacy decision making by showing its lasting effects over time. By extending our consideration to repeated choices, we are able to better model the progression of individuals' privacy behavior. Finally, with the exception of Peer and Acquisti (2016), to our knowledge, no other work has addressed the role of reversibility in privacy decision making. We show how explicit reversibility or irreversibility can alter an individual's perception of privacy risk and their willingness to forgo anonymity online. This answers the call for further exploration of the effects of two seemingly opposite constructs put forth by Peer and Acquisti (2016). We relate the effect of reversibility to that of control and how literature has primarily considered control's effect on gaining initial consent, not preventing a revocation of consent (Whitley 2009).

We also contribute to the literature in behavioral economics and choice architecture. First, we reiterate past findings that show the power of default effects, specifically as they relate to an active choice structure (Letzler et al. 2017; Li et al. 2013). Second, we explore the persistence of choice defaults across instances of exposure. Despite extensive consideration around default effects, little is known about their ability to persist over time (Marteau et al. 2011). The little evidence that has been presented primarily focuses on the persistence of a single exposure to a default effect (Venema et al. 2018). Our consideration allows for a more thorough understanding of the effect of defaults over time, specifically in light of multiple presentations of the same default. Finally, to the best of our knowledge, no work has evaluated the combined effect of explicit reversibility and choice defaults. This consideration grants further insight to the changing effects of choice defaults when paired with other interventions.

Finally, we contribute to the growing literature surrounding the implications of broad privacy regulation like GDPR (Adjerid et al. 2015; Batikas et al. 2020; Goldberg et al. 2019; Jia et al. 2018). To our knowledge, this is the first work to consider the interactive effects of specific tenets of privacy regulation such as repeated exposure and reversibility. We isolate these specific enactments to better understanding the far-reaching implications of emerging privacy law. Our experimental approach allow us to focus on key aspects of new legislation (as opposed to consider these laws as one shock) and extend the current conversation around new privacy-related legislation and addresses concerns relating to specific aspects of these laws. We further contribute to the literature by showing the importance of reversible consent and its impact on consumer behavior.

For firms, our findings are important when navigating the changing regulatory structure and when designing user interfaces that abide by said regulation while not being prohibitively costly to the firm. Understanding the consumer decision-making process can assist firms in designing appropriate interfaces that remain protective while still allowing for considerable rates of consent. Additionally, we highlight the balance between protectiveness and economic benefit that is impacted by privacy regulation. Policymakers can use these findings to design regulation that balances the two considerations and apply them to specific choice contexts. For instance, one interpretation of our findings is that while each of the changes to how consent is elicited can have the desired policy impact (consumers choosing options that better reflect their privacy concerns), the scale of our effects suggest that a combination of protective defaults, reversibility, and repeated exposure may lead to an overreaction from consumers with respect to consent. Finally, consumers benefit from a more thorough understanding of their own decision biases when presented with privacy choices. These findings can assist consumers in understanding the far reaching implications of consent decisions and navigating changing choice architectures in light of new privacy regulation.

2. Conceptual Background & Hypotheses

This study examines and builds on three existing areas of research. The first is privacy decision making, an area of research that has grown in complexity within the last several decades (Bélanger and Crossler 2011; Li 2011; Pavlou 2011). While any number of factors may influence the outcome of a privacy decision, this work specifically focuses on a second area of research, choice architecture – the idea that subtle changes in the design of a choice can drastically impact the behavior and decision making of an individual presented with that choice (Egelman et al. 2013; Johnson et al. 2012; Keller et al. 2011; Thaler et al. 2013). At the intersection of these two streams, we consider the effect of choice architecture on privacy decision making and how its effect may be influenced the repetitiveness and reversibility of the decision.

The information systems literature is increasingly adopting insights and rationale from behavioral economics (Goes 2013). The traditional view within behavioral economics has been that decision makers operate through a rational process, driven by the desire to maximize utility (Mullainathan and Thaler 2000). When applied to privacy decision making, this gave rise to the development of a privacy calculus, in which consumers systematically weighed the costs and benefits of privacy-related disclosures (Dinev and Hart 2006).

More recent research has softened these assumptions and posits that privacy choices are driven by both deliberative assessments of benefits and risks as well as by bounded rationality and cognitive biases (Acquisti et al. 2012; Li et al. 2008; Tsai et al. 2011). Manipulations in the presentation of a choice, termed choice architecture, take advantage of these biases in order to encourage particular decision outcomes. Major findings surrounding the powerful effects of choice architecture have been highlighted extensively in the literature (Egelman et al. 2013; Johnson et al. 2012; Keller et al. 2011; Thaler et al. 2013).

In light of these findings and given the importance of privacy decision making to consumer outcomes, we aim to further explore the impacts of choice architecture. We focus specifically on one powerful and relevant application of choice architecture, choice defaults and how choice defaults intersect with both the repetitiveness and reversibility of many privacy decisions.

2.1.1 Choice Defaults

As defined by the choice architecture literature, a default is the first considered option when making a decision and is the "status quo" for the decision maker before they consider other options (Huh et al. 2014). Generally, defaults are presented with one option as the opt-out choice (meaning that the decision maker must exert effort to change their decision from that choice; e.g. the default) and all others as opt-in (Johnson and Goldstein 2003). Decision makers presented with these defaults are given a default configuration that they can then add or subtract features from (Park et al. 2000). Defaults could also present as a choice between two options but where only one is given and the other must be requested (McKenzie et al. 2006).

Whichever way a default is presented, extensive evidence exists showing that this specific choice architecture will have significant effects on consumer outcomes (Johnson et al. 2002; Johnson and Goldstein 2003; Thaler and Sunstein 2008). A classic example in the literature shows how presenting an organ donation decision with an opt-in design can drastically alter the decision maker's willingness to donate (Johnson and Goldstein 2003). Similar effects have been shown for consumer product choices among other decisions (Brown and Krishna 2004; Dinner et al. 2011).

Discussions on the causes of defaults have provided a number of valuable findings. First, a default choice is often "easy." Identifying the best option among choices and analyzing underlying tradeoffs takes time and increases cognitive effort (Tversky and Kahneman 1974), whereas no effort is required of the decision maker when a default choice is presented. A decision maker exhibiting cognitive laziness may be more susceptible to a less effortful choice (Fiske and Taylor 1991; Samuelson and Zeckhauser 1988; Thaler and Sunstein 2008). Consumers have shown this affinity for less effortful choices when alternatives require higher levels of cognitive effort (Brown and Krishna 2004; Camerer et al. 2003; Johnson et al. 2002). Additionally, when decision makers are tired (Levav et al. 2010) or when their self-control has been taxed (Evans et al. 2011) they have shown to be more susceptible to defaults. These effort based accounts show that default effects are most impactful when people fail to align the effort required to make the choice with the importance of its outcome (McKenzie et al. 2006).

Additionally, research on social influence has been used to describe the effects of defaults (Huh et al. 2014). It has been shown that decision makers often view default choices as an implicit recommendation on the part of the person or organization that is giving them that choice (Brown and Krishna 2004; McKenzie et al. 2006). Defaults have an inherently social nature, that can be exploited by (1) the belief that the behavior of others provides "diagnostic information" [informational influence] and (2) the desire of an individual to adhere to the expectations of society [normative influence] (Deutsch and Gerard 1955). Informational influence is based on an individual's desire to be accurate (e.g. they believe that others give information that is evidence about reality) and normative influence is based on the desire to behave "appropriately in a social setting" (Campbell and Fairey 1989; Cialdini and Goldstein 2004). Huh et al. (2014) show that "social defaults" arise outside of conscious awareness. However, these automatic processes can be disrupted when decision makers have the cognitive resources necessary to think through their decisions (Bargh 1994; Fiske 1998).

Given the extensive findings on default effects and identifying our choice context as the decision to log-in to a webservice, we hypothesize that:

H1a: *Presenting a log-in decision as an active choice will result in lower log-in rates when compared with a default opt-in.*

H1b: *Presenting a log-in decision as a default opt-out will result in lower log-in rates when compared with either an active choice or a default opt-in.*

2.1.2 Reversibility

This study considers the role of reversibility in privacy policy requirements. We explore how reversibility changes a person's willingness to consent along with its interaction with choice architectures. Allowing for reversible consent is a central tenet of most modern privacy regulation, most notably GDPR (Article 29 2017). These changes are intended to grant further control to consumers over their privacy. Giving consumers control over their personal data is an essential aspect for maintaining privacy related trust (Whitley 2009). When trust in an online entity is high, individuals tend to make riskier privacy decisions (Lauer and Deng 2007). This has the potential to show that allowing for reversible consent makes consumers more willing to disclose of personal information initially online, even if the disclosure is risky.

However, most reversibility-related empirical conclusions drawn from literature are outside of the scope of online privacy. For example, it has been shown that consumers have greater trust in retailers when they have more lenient return policies (Bonifield et al. 2010). Few findings exist that substantiate reversibility as a trust-invoking element of control within online privacy. By contrast, the evidence that does exist, primarily shows the reverse. Peer and Acquisti (2016) show that reversibility instead cues the individual as to the seriousness of the decision at hand. This leads to less risky decision making in the form of less disclosure. Additionally, they show that both reversibility and irreversibility have the same directional effect, so long as they are made salient. While individuals may still prefer a reversible decision, this does not entice them to disclose more as it entices them to, say, purchase more from a vendor (Wood 2001).

Applying these results to choice architecture gives rise to a number of interesting conclusions. First, when making a decision explicitly reversible or irreversible, consumers' perceived stakes of the decision rise. This leads to lower rates of fatigue and lower cognitive laziness, two important drivers of default effects. However, given the implicit preference for reversible choices shown extensively in the extant literature, individuals may feel more comfortable with a reversible choice, leading to higher rates of cognitive laziness. Therefore, we expect that salient reversibility may increase the effect of defaults while irreversibility may lessen those effects.

H2a: *Informing a decision maker of the reversibility of a decision will increase the effects of choice defaults.*

H2b: *Informing a decision maker of the irreversibility of a decision will decrease the effects of choice defaults.*

2.1.3 Experiential Effects

While the use of choice architecture and the effects of defaults have been introduced to the privacy decision making literature (Adjerid et al. 2019; Almuhimedi et al. 2015; Ariely and

Holzwarth 2017), few works exist that evaluate its impact on decision making and, to our knowledge, the works that do exist focus solely on one-off choices. In reality, privacy policy requirements, such as consent re-elicitation, require uses to make a privacy choice numerous times, likely influencing consumers' decision-making processes. We address this gap in the literature by considering the effect of repeated privacy choices on the impact of choice defaults.

When presented with the same privacy choice numerous times, decision makers have the potential to rethink the decision as they gain experience in the choice context. This is critical to the impact of choice defaults (and other manipulations of choice architecture) since the repetition of these choices has the potential to improve consumer outcomes and their choice-making "muscles" can be exercised to think through and make better decisions (York et al. 2018). In particular, realizing the consequences of past decisions and gaining new information can result in a revised belief system that may change the outcome of the decision the next time it is presented (Carlsson et al. 2012; Hagmayer and Meder 2013).

Critically, some of the prior literature has shown that an individual can learn to overcome behavioral biases typically leveraged by choice architecture (e.g. the status quo bias) (Sellier et al. 2019; Smith 1976; Smith 1982). Learning to make better privacy decisions often comes from receiving feedback from the choice context to encourage a revision of one's belief system (Lagnado et al. 2007). Specific to privacy, tools meant to increase privacy awareness can be sub-optimally configured if they lack proper feedback for their users (Leon et al. 2012). Further complicating the matter, feedback that pushes users' existing causal models might irritate the user and have the opposite of the intended effect (i.e. strict password suggestion meters) (Ur et al. 2012).

However, the current literature is divided on the impact of repetition on decision making. Despite the above findings, others have shown that behavioral biases persist, or even strengthen, when individuals make repeated choices. More so, repetition of choices can introduce new decision biases; for example, (Schaub et al. 2015) find that habituation in repeated choice contexts prevents the retrieval of new information. Past literature has shown that individuals exhibit what has been termed “privacy fatigue,” where they disclose more information over time when faced with increasing complexity and less usability in privacy controls (Keith et al. 2014). Choi et al. (2018) show how privacy fatigue leads to a perceived loss of control and a sense of futility with protecting one’s privacy that results in less informed privacy decision making. This theory has also been applied to privacy and security notices (Schaub et al. 2015). When the complexity of a notice is high and there is a lack of choices, it becomes unimportant to the consumer (Cate 2010). Individuals who see these seemingly unimportant notices repeatedly tend to habituate to the notices and dismiss them without any consideration (Anderson et al. 2015).

Given that two key mechanisms underlying default effects are (1) cognitive laziness and (2) social norm adherence, we can consider how experience in a choice context would impact these effects. Experience may lead to the collection of new information, a refinement of preferences, and a resulting revision of belief systems. This could make an individual less susceptible to default effects. However, as stated above, repetitive complex choices may lead to privacy fatigue. In addition, complex decisions require more cognitive effort which is undesirable to decision makers. As a primary cause of default effects, it would follow that privacy fatigue from multiple choice presentations and the cognitive effort required of each decision would have at least an additive effect on the impact of defaults. Additionally, some evidence exists to show that the subtle pressure to adhere to social norms increases over time

(Sen and Airiau 2007). If the pressure to adhere to social norms increase with experience, then the effect of defaults should strengthen with experience as well.

The lack of work evaluating the experience with a privacy context in addition to the intersection of experience and choice architecture in the privacy decision making literature is a significant research gap with important implications for research and practice. Upon review of the existing literature, we hypothesize that:

H3: *Experience in a choice setting will result in an increased effect of choice defaults.*

3. Experimental Design

3.1 Two Factor Between-Subjects Design

We conducted a two factor between-subjects online experiment to evaluate our hypotheses[6]. We chose to conduct an online experiment, instead of analyzing secondary data, so that causal relationships could be developed without interference from endogeneity and so that we could achieve a level of precision not possible otherwise (Gupta et al. 2018). Our two factors differentiated 1) the structure of consent retrieval and 2) the structure of consent reversal. We also considered a third factor experimental factor to exogenously shift an individual's level of social desirability bias (SDB). The intervention did not have an effect on behavior and is not included in our analysis for clarity. Because these are exogenous manipulation, their inclusion/exclusion does not impact the estimates for other treatment conditions (Appendix A shows consistent results while controlling for attempted manipulations of SDB).

3.1.1 Consent Retrieval

[6] An earlier iteration of this paper attempted to exogenously shift social desirability bias in addition to manipulating consent retrieval and consent reversal, making our experiment a three-factor design. This attempt proved unsuccessful and our SDB conditions had no effect on the outcomes of our other factors.

Participants were first separated into three dimensions for consent retrieval: default logged-in (our control dimension, indicative of the traditional universal opt-in structure), active choice (the structure required by privacy policy such as GDPR), and default not logged-in (a highly protective opt-out privacy structure). Participants in the opt-in and opt-out groups were presented with one choice for the log-in decision: “Sign into my research profile” or “Continue as guest” respectively. In either case, the option was pre-selected. If the participant wanted to change the selection, they had to manually uncheck the box. In the active choice dimension, they were presented with both of the above options: “Sign into my research profile” and “Continue as guest.” Neither option was pre-selected, requiring these participants to manually choose one of the two options. Participants were presented with this choice three times, holding the consent structure constant, to measure the change in structure effects that comes with experience in a choice context. The three default presentations can be seen in Figures 1a-1c.

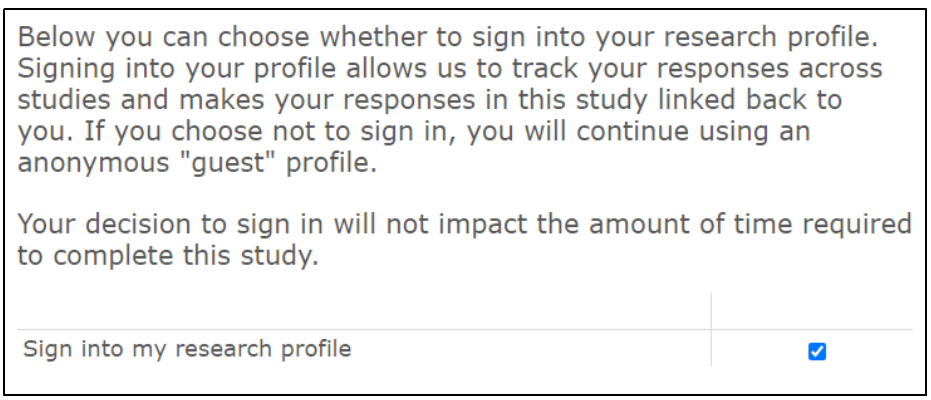


Figure 1a: Opt-in default presentation

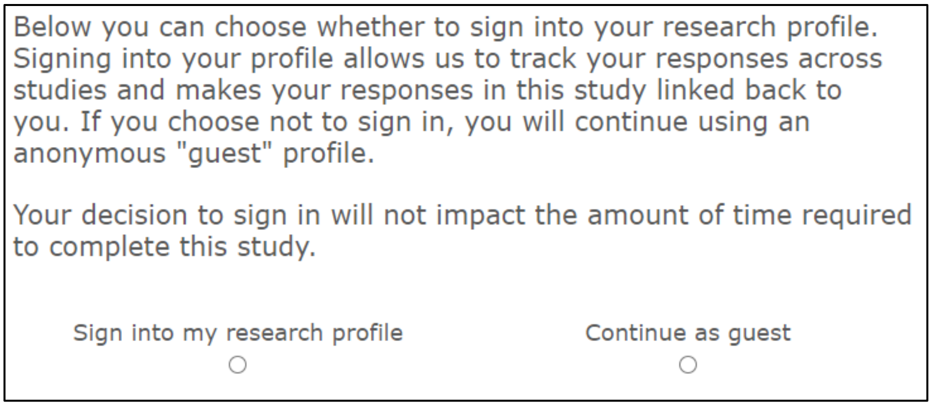


Figure 1b: Active choice default presentation

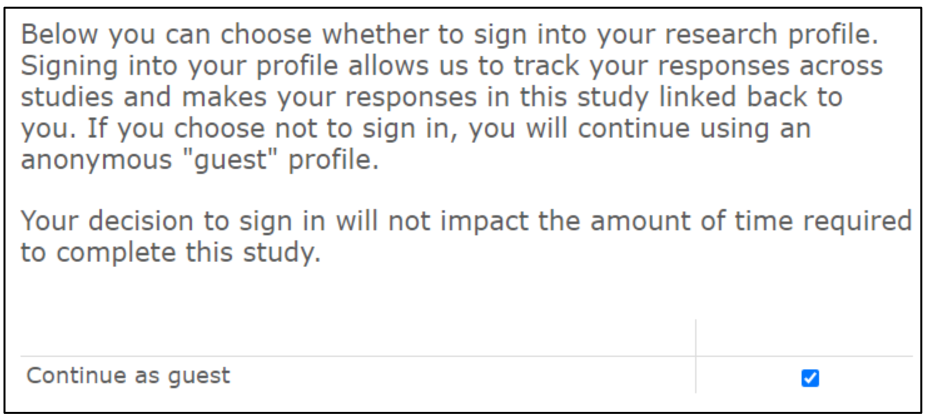
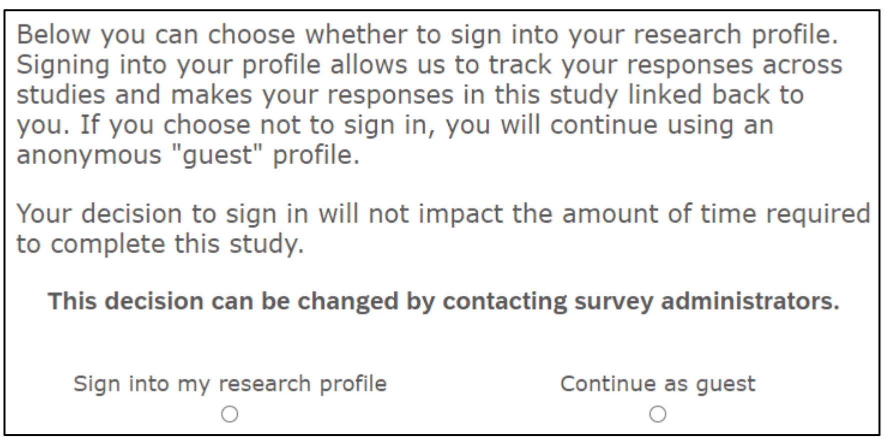


Figure 1c: Opt-out default presentation

3.1.2 Consent Reversal

We also manipulated the reversibility of the log-in decisions. Each participant saw their log-in decision presented with one of three options: a statement making the reversibility of the log-in decision explicit, a statement making the irreversibility of the log-in decision explicit, or no statement regarding reversibility (our control dimension). The reversible statement read, “This decision can be changed by contacting survey administrators.” Conversely, the irreversible statement informed the participant that, “This decision cannot be changed and is final.” Examples of these statements can be seen in Figures 2a and 2b. These figures display the reversibility/irreversibility statements for those in the active choice default dimension. It is important to note that those in the opt-in default dimension and the opt-out default dimension were divided in the same way.


Below you can choose whether to sign into your research profile. Signing into your profile allows us to track your responses across studies and makes your responses in this study linked back to you. If you choose not to sign in, you will continue using an anonymous "guest" profile.

Your decision to sign in will not impact the amount of time required to complete this study.

This decision can be changed by contacting survey administrators.

Sign into my research profile ○ Continue as guest ○

Figure 2a: Reversible presentation

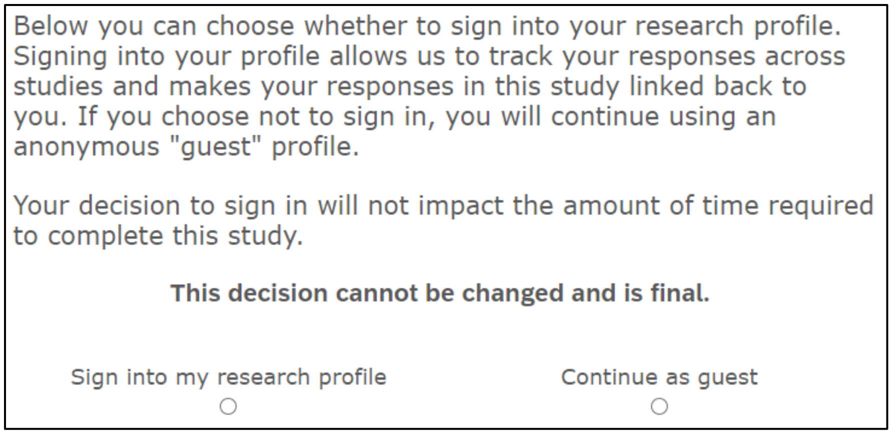


Figure 2b: Irreversible presentation

3.2 Participants and Procedure

We recruited 1600 participants for this experiment. After filtering out participants that did not complete the entirety of the study, participants that gave non-engaged responses, and participants that asked for their data to be removed after debriefing, 1526 participants were left. Participants were recruited through Prolific, an online subject recruitment platform that specifically caters to researchers, unlike the more commonly used Amazon Mechanical Turk (AMT) (Palan and Schitter 2018). Prolific has been shown to provide data quality comparable to AMT while providing participants that are more naïve to “common experimental research tasks” (Peer et al. 2017). Participants were compensated $3.40 upon completing all three studies.

Participants began by creating a research profile. The profile consisted of two parts. The first part included demographic information such as gender, ethnicity, geographical location, and education/work status. The second part asked participants to complete an evaluation that measured social desirability bias.[7] This research profile simulated a personal profile that one would create on a popular web service.

Participants were then directed to take three studies, in a random order. Participants were informed at the beginning of each study that we were exploring potentially unethical behavior and that some of the questions that would be asked dealt with adult or sensitive material. The participants were also informed that they may skip any questions that they wish not to answer. The three studies contained questions related to criminal activity, sexual activity, and romantic involvement, respectively. These studies were randomly ordered and counterbalanced. The questions asked in each study can be found in Appendix B.

The experiment was designed to mimic a user's repeated interactions with an online webservice. Measures were taken to ensure that the participants felt that each study was separate and unique. First, each of these studies began by providing the consent form which listed details related to the study, requirements, risks, benefits, and compensation. The consent form was provided three times to give the impression to the participants that each study was different from the previous one. Second, each study had a different theme (e.g. colors, fonts, layouts). Finally, at the end of each study, participants were asked to watch a video relating to the context of the specific study that acted as a time lag between studies.

At the onset of each study, the participants were given the choice to log-in to their research profile before answering the questions. Depending on their randomly assigned condition, this choice was presented as either defaulted to log-in (the control group), an active choice to either log-in or not, or defaulted to remain as a "guest" (see Figures 1a-1c). They were

[7] Prior to completing this evaluation, participants watched one of three videos that were intended to shift SDB. These videos had no effect on log-in rates across conditions (see Appendix A)

informed that logging-in would allow us to track their responses and that by doing so, their responses would be linked back to them. To make the decision salient, participants who chose to sign into their research profile saw their Prolific ID listed at the top of each subsequent page of the study. Participants who chose to not login saw “Guest” listed instead. Additionally, the participants either saw a statement making the choice explicitly reversible, explicitly irreversible, or no statement (the control group)—see Figures 2a-2b. The conditions related to defaults and reversibility remained the same for the respective participant across each of the studies.

The participant then was directed to a series of 5 questions related to the study topic. After the 5 questions were answered, they were shown a short video that they had to watch and subsequently summarize and reflect on. They were then randomly directed to one of the remaining studies. At the conclusion of the third and final study, they were asked a set of exit questions (Appendix C) and were then debriefed to let them know that they were participating in one study, not three separate studies as we had led them to believe.

The participant’s decision to log-in and their level of disclosure (e.g. the number of unethical behaviors they admitted to having done) was measured across the three studies. This was intended to measure the impact that experience has on the effect of differing structures of consent retrieval. In addition, the effect of differing structures of consent reversal was measured both initially and over time.

4. Analysis

4.1 Balance Check

We evaluate observable variables for each participant (age, race, gender, education, and employment) and find balance across most variables. The primary exception is gender across default and reversibility conditions. We show that the inclusion of these controls in the analysis has no bearing on our results. Descriptive statistics and a table of pairwise comparisons are in Appendix D.

4.2 Initial Effect of Changing Choice Architecture

4.2.1 Estimation Approach

The dependent variable in our regression is a binary indicator variable that represents whether or not the participant *i* chose to log-in to their research profile. For our initial consideration of default effects, we consider the participant's first exposure to the choice.

$$LogIn_i = \beta_1 ActiveChoice_i + \beta_2 OptOut_i + \boldsymbol{\alpha_i DEM} + \gamma_i + u_i$$

$ActiveChoice_i$ is a binary indicator for whether or not a participant was in an active choice condition. $Opt\text{-}Out_i$ is a binary indicator for whether or not a participant was in an opt-out condition. Additionally, we control for participant demographics (age, gender, race, education, and employment) and include study context fixed effects (e.g. Sex, Romance, Crime) γ_i Estimates on randomly assigned treatments are unbiased due to assumed exogeneity of experimental manipulations.

4.2.2 Results

One thousand five hundred and twenty-six participants from Prolific took part in our experiment. Our control group (opt-in) had expectedly the highest baselines for log-in percentage. This shows the consequences of a universal opt-in structure for consent retrieval that resulted in roughly 92% of participants in these groups choosing to log-in during their first exposure to the choice. Both the active choice conditions and the protective opt-out conditions had strong initial effects. An active choice structure decreased initial log-in rates in Study 1 by 11.5%. The protective opt-out conditions decreased initial log-in rates by 41%. This confirms hypotheses **H1a** and **H1b**. Figure 3 is a graphical representation of the results and Table 1 shows estimates of our above model with and without demographic controls.

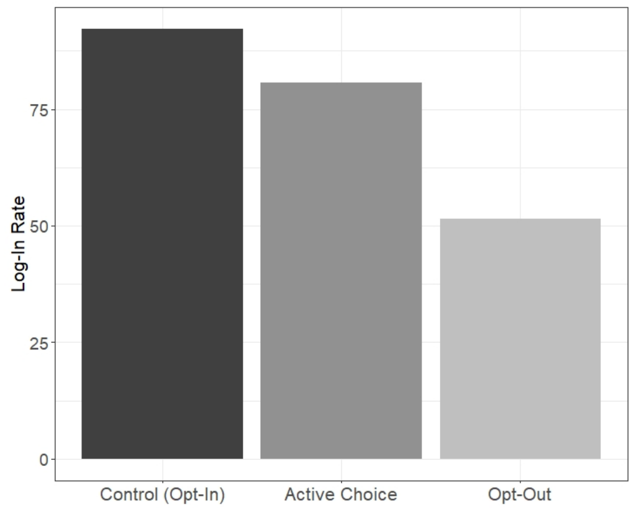


Figure 3: Log-In Rates Across Consent Retrieval Structure

VARIABLES	(1) Log-In	(2) Log-In
Active Choice	-0.115***	-0.115***
	(0.0211)	(0.0212)
Opt-Out	-0.409***	-0.409***
	(0.0254)	(0.0256)
Constant	0.916***	0.923***
	(0.0271)	(0.0468)
Controls	No	Yes
Context FE	Yes	Yes
Observations	1,526	1,526
R-squared	0.158	0.161

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1: Initial Regression Results (Consent Retrieval)

4.3 Effect of Consent Reversal Structure on Choice Architecture

4.3.1 Estimation Approach

The dependent variable in our second regression is the same binary indicator used above. For our initial consideration of reversibility and default effects, we consider the participant's first exposure to the choice.

$$LogIn_i = \beta_1 ActiveChoice_i + \beta_2 OptOut_i + \beta_3 Reversible_i + \beta_4 Irreversible_i$$

$$+\beta_5 ActiveChoice_i \times Reversible_i + \beta_6 ActiveChoice_i \times Irreversible_i$$

$$+ \beta_7 OptOut_i \times Reversible_i + \beta_8 OptOut_i \times Irreversible_i + \boldsymbol{\alpha_i DEM} + \gamma_i + u_i$$

$Reversible_i$ is a binary indicator for whether or not a participant was in a reversible condition. $Irreversible_i$ is a binary indicator for whether or not a participant was in an irreversible condition. We also include interaction terms between the consent retrieval and consent reversal structures.

4.3.2 Results

Our analysis first confirms significant initial effects of consent retrieval structure. When there is no explicit reversibility or irreversibility, an active choice structure decreases log-in rates by 12% and an opt-out default structure decreases log-in rates by 34%. Most notably, our results show us that when paired with an opt-out default structure, both reversibility and irreversibility decrease log-in rates by an additional 11%.

Additionally, neither reversibility nor irreversibility has an effect on an opt-in default structure or an active choice structure. This implies that reversibility and irreversibility do act as a cue as to the seriousness of the decision being made. However, this seriousness is only made salient if the participant is also given a default opt-out structure (which selects the protective option). Our results provide partial support for **H2**, showing that neither reversibility nor irreversibility has an effect on an opt-in default but both strengthen the effect of an opt-out default. Table 2 shows the preliminary analysis for the effect of consent reversal structure in Study 1 with and without controls and Figure 4 is a graphical representation of the results.

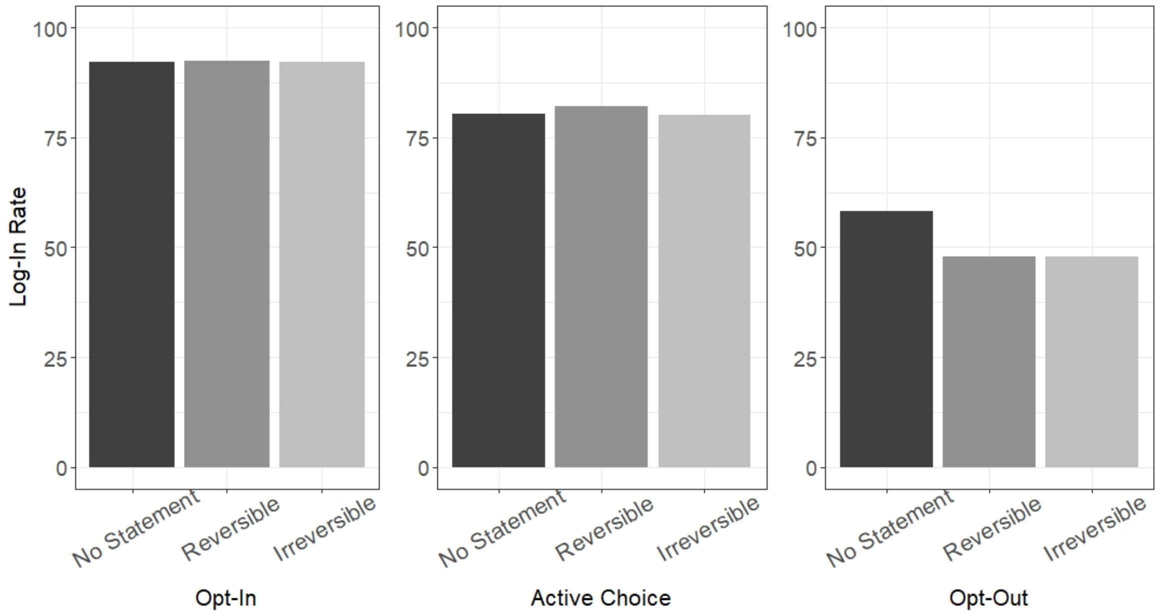


Figure 4: Log-In Rates Across Consent Retrieval & Consent Reversal Structure

VARIABLES	(1) Log-In	(2) Log-In
Active Choice	-0.120***	-0.118***
	(0.0376)	(0.0379)
Opt-Out	-0.339***	-0.336***
	(0.0434)	(0.0435)
Reversibility	0.000952	0.00205
	(0.0286)	(0.0291)
Irreversibility	0.000332	0.000859
	(0.0288)	(0.0288)
Active*Reversibility	0.0170	0.0147
	(0.0519)	(0.0527)
Active*Irreversibility	-0.00270	-0.00485
	(0.0523)	(0.0524)
Opt-Out*Reversibility	-0.106*	-0.112*
	(0.0620)	(0.0624)
Opt-Out*Irreversibility	-0.105*	-0.109*
	(0.0618)	(0.0619)
Constant	0.916***	0.923***
	(0.0329)	(0.0501)
Controls	No	Yes
Context FE	Yes	Yes
Observations	1,526	1,526
R-squared	0.163	0.165

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Initial Regression Results (Consent Reversal)

4.4 Effect of Experience on Choice Architecture

4.4.1 Estimation Approach

The dependent variable in our third regression is the same binary indicator used above. This log-in decision is a repeated measure and therefore we use a panel random effects regression for our estimation.

$$LogIn_{ij} = \beta_1 ActiveChoice_i + \beta_2 OptOut_i + \beta_3 StudyNumber_{ij}$$

$$+ \beta_4 ActiveChoice_i \times StudyNumber_{ij} + \beta_5 OptOut_i \times StudyNumber_{ij} + \gamma_{ij} + \boldsymbol{\alpha}_i + u_i$$

$StudyNumber_{ij}$ is a continuous variable representing whether the participant is partaking in their first, second, or third study. This variable evaluates the impact over time for the baseline condition (opt-in). We also include interaction terms between study number and choice architecture. To first isolate the effects of experience, we estimate three separate models, controlling for reversibility condition.

4.4.2 Results

The results of our analysis can be found in Table 3 and Table 4 below. We first break down the regression by each of the three studies, controlling for the reversibility condition. Table 3 estimates the model only for those that were shown no statement on reversibility or irreversibility. The first three columns show the effects of choice architecture across the three studies. The log-in rate for the control condition (shown by the constant) is 92.3%, 95.2%, and 95.8% respectively. This shows an increasing effect of an opt-in default. Likewise, the effect of a protective opt-out default is -33.9%, -39.9%, and -40.5% respectively. This shows an increasing effect of an opt-out default (decreasing log-ins over time). Columns 4-6 estimate the same model with demographic controls included to show the consistency of our results. Finally, Column 7 is the estimated panel data model. This estimation assigns significance to our results. The coefficient on $StudyNumber_i$ represents the effect of experience on the opt-in default, showing that for each study, participants log-in 1.78% more ($p<0.05$). The interaction term between the study number and the protective opt-out default is also significant ($p<0.05$) and shows an additional -3.27% decrease in log-in rates for each study.

Table 4 shows the same analysis for those in either the reversible or irreversible conditions. Interestingly, the increase in default effects was not replicated for these participants. We combine reversible and irreversible conditions due to their similar directional effects. Appendix E shows this analysis broken down further by reversible and irreversible.

Our results show that in absence of explicit reversibility or irreversibility, individuals may be subject to some level of fatigue that allows the effects of defaults to grow. However, when the same decision is made reversible or irreversible, while there is an initial decrease in log-in rates, the effects of the defaults do not grow over time. Therefore, we can partially confirm **H3** that experience does increase the effect of defaults, however with the caveat that this result only holds when the decision is not explicitly reversible or irreversible. Similar to Peer and Acquisti (2016), our interpretation of these results is that reversibility introduces privacy concerns for consumers. However, these concerns affect the two default options differently. For those in the opt-in group, the elevated concerns diminish the propensity of permissive defaults to increase opt-in over time. For the protective opt-out group, consent is driven down significantly by reversibility, perhaps introducing ceiling effects. In other words, most who would be impacted by the default observe that effect immediately and this large effect persists, but does not grow, over time.

	No Statement	No Statement	No Statement	No Statement	No Statement	No Statement	No Statement
	(Study 1)	(Study 2)	(Study 3)	(Study 1)	(Study 2)	(Study 3)	(Panel)
VARIABLES	Log-In	Log-In	Log-In	Log-In	Log-In	Log-In	Log-In
Active Choice	-0.120***	-0.144***	-0.137***	-0.115***	-0.135***	-0.126***	-0.108**
	(0.0376)	(0.0351)	(0.0339)	(0.0386)	(0.0361)	(0.0348)	(0.0442)
Opt-Out	-0.339***	-0.399***	-0.405***	-0.333***	-0.392***	-0.399***	-0.309***
	(0.0434)	(0.0419)	(0.0415)	(0.0441)	(0.0424)	(0.0416)	(0.0501)
Study Number							0.0178**
							(0.00835)
Active*Number							-0.00848
							(0.0116)
Opt-Out*Number							-0.0327**
							(0.0136)
Constant	0.923***	0.952***	0.958***	0.922***	1.061***	1.089***	0.865***
	(0.0207)	(0.0165)	(0.0155)	(0.0940)	(0.0897)	(0.0888)	(0.0803)
Controls	No	No	No	Yes	Yes	Yes	Yes
Context FE	No	No	No	Yes	Yes	Yes	Yes
Observations	498	498	498	498	498	498	1,494
R-squared	0.112	0.156	0.165	0.120	0.170	0.180	
Number of ID							498

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Effect of Experience on Choice Architecture (No Reversibility or Irreversibility)

	Reversible or Irreversible	Reversible or Irreversible	Reversible or Irreversible	Reversible or Irreversible	Reversible or Irreversible	Reversible or Irreversible	Reversible or Irreversible
	(Study 1)	(Study 2)	(Study 3)	(Study 1)	(Study 2)	(Study 3)	(Panel)
VARIABLES	Log-In	Log-In	Log-In	Log-In	Log-In	Log-In	Log-In
Active Choice	-0.113***	-0.119***	-0.116***	-0.114***	-0.120***	-0.118***	-0.115***
	(0.0254)	(0.0254)	(0.0260)	(0.0259)	(0.0259)	(0.0264)	(0.0272)
Opt-Out	-0.445***	-0.463***	-0.461***	-0.446***	-0.463***	-0.460***	-0.441***
	(0.0312)	(0.0310)	(0.0313)	(0.0315)	(0.0312)	(0.0315)	(0.0339)
Study Number							-0.00289
							(0.00390)
Active*Number							-0.00157
							(0.00586)
Opt-Out*Number							-0.00795
							(0.00837)
Constant	0.923***	0.926***	0.918***	0.903***	0.899***	0.819***	0.879***
	(0.0140)	(0.0138)	(0.0144)	(0.0644)	(0.0596)	(0.0642)	(0.0540)
Controls	No	No	No	Yes	Yes	Yes	Yes
Context FE	No	No	No	Yes	Yes	Yes	Yes
Observations	1,028	1,028	1,028	1,028	1,028	1,028	3,084
R-squared	0.184	0.197	0.193	0.188	0.201	0.199	
Number of ID							1,028

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Effect of Experience on Choice Architecture (Explicit Reversibility or Irreversibility)

4.5 Effects on Disclosure

The above regressions were estimated replacing the dependent variable, $LogIn_i$, with $Disclosure_i$, an ordinal variable (1-5) representing the level of disclosure for each participant *i*. In each study, 5 questions were asked pertaining to potentially incriminating behavior. The value in $Disclosure_i$ is a summation of each behavior the participant admitted to partaking in. We start by only considering a participant's first exposure to the choice.

$$Disclosure_i = \beta_1 ActiveChoice_i + \beta_2 OptOut_i + \boldsymbol{\alpha}_i \boldsymbol{DEM} + \gamma_i + u_i$$

4.5.1 Initial Effect of Changing Choice Architecture on Disclosure

Considering the effect of choice architecture on subsequent disclosures, initial exploration appears to show increasing disclosure as choice architecture gets more protective. Those in the universal opt-in, active choice, and protective opt-out conditions disclosed 2.04, 2.10, and 2.21 behaviors on average, respectively. This is shown in Figure 5 below.

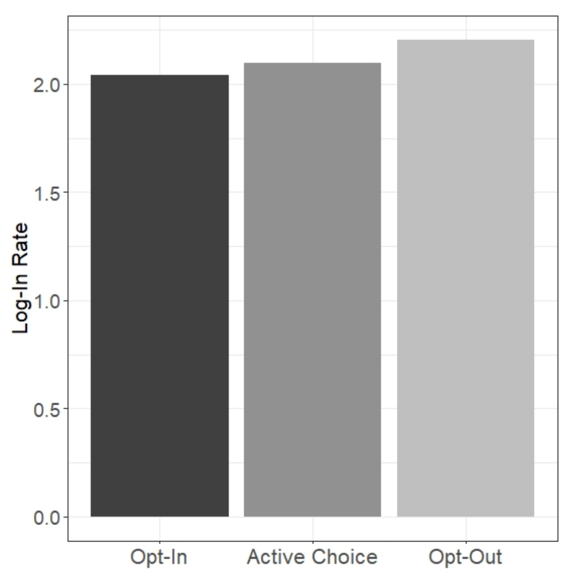


Figure 5: Disclosure Across Choice Architectures

Despite the visual trend in disclosure rates across choice architectures, initial regression results do not show significant effects. These regression results can be seen in Table 5 below with and without demographic controls. This is consistent with prior work suggesting that subtle changes to choice architecture can have powerful impacts on initial privacy choices that do not translate to downstream changes in disclosure (Adjerid et al. 2019).

VARIABLES	(1) Disclosure	(2) Disclosure
Active Choice	0.0590	0.0838
	(0.0888)	(0.0882)
Opt-Out	0.137	0.145
	(0.0909)	(0.0902)
Constant	0.839***	0.798***
	(0.108)	(0.185)
Controls	No	Yes
Context FE	Yes	Yes
Observations	1,526	1,526
R-squared	0.108	0.126

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Effect of Choice Architecture on Disclosure

4.5.2 Effect of Consent Reversal Structure on Disclosure

We estimate the above model replacing $ActiveChoice_i$ and $OptOut_i$ with $Reversible_i$ and $Irreversible_i$, respectively. Table 6 shows the estimated model with and without controls. Interestingly, both reversibility and irreversibility have significant positive effects on disclosure ($p \approx 0.10$ and $p < 0.05$). These effects could be the result of lower log-in rates for those in reversible or irreversible conditions, therefore leading to higher rates of disclosure.[8] These findings highlight that while reversibility can decrease up front consent, unlike subtle changes to

[8] Given that the log-in choice is an intermediate outcome, we do not include it as a regressor in our model.

choice architecture, it can have important compensatory reactions by consumers that make them more open to disclosing information in downstream choices. This result points to an important distinction between a salient stimulus that impacts upstream privacy choices vs. more subtle stimuli (e.g. changes in choice defaults) which can influence users to be more privacy conscious but will not result in more openness in other downstream choices made by consumers.

VARIABLES	(1) Disclosure	(2) Disclosure
Reversibility	0.152*	0.130
	(0.0910)	(0.0906)
Irreversibility	0.230**	0.211**
	(0.0900)	(0.0896)
Constant	0.763***	0.746***
	(0.107)	(0.185)
Controls	No	Yes
Context FE	Yes	Yes
Observations	1,526	1,526
R-squared	0.110	0.128

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Effect of Reversibility and Irreversibility on Disclosure

5. Discussion & Conclusion

5.1 Theoretical and Research Implications

These findings contribute to the privacy decision making literature. Specifically, past work has primarily focused on one-off choices (Acquisti and Grossklags 2005), thus, we extend work on the influence of biases in privacy decision making by showing its lasting effects over time. Additionally, with the exception of Peer and Acquisti (2016), to our knowledge, no other work has addressed the role of reversibility in privacy decision making. We also contribute to the literature in behavioral economics and choice architecture by exploring the persistence of choice defaults across instances of exposure. In addition, to the best of our knowledge, no work has evaluated the combined effect of explicit reversibility and choice defaults. Finally, we contribute to the work considering the far-reaching implications of GDPR and similar changes in privacy regulation (Adjerid et al. 2015; Goldberg et al. 2019; Goldfarb and Tucker 2011b; Johnson and Shriver 2020; Miller and Tucker 2009; Miller and Tucker 2017). To our knowledge, this is the first work that considers the interactive effects of changes enacted by privacy policies with experiential effects and the effects of stated reversibility.

There are three main limitations to our study. First, our work is likely subject to ceiling effects with respect to measuring the effect of default opt-in choices. Further work is needed to better understand the persistence of these default effects over time. Second, we did not measure the effect of changing choice architecture with respect to specific decision biases. Evaluating this effect with regards to cognitive laziness, privacy fatigue, and other biases will lend a clearer understanding of this phenomenon. Finally, our work was done in an isolated environment where the risks of disclosure, while real, were not overly intrusive. Expanding these ideas to a field environment where real life privacy decisions are being made would grant further credence to the results.

Future research can contribute to these results and expand their scope. First, the privacy decision making literature can benefit from analyzing interactive effects on behavior. This study considers the interaction between defaults and experience and defaults and reversibility. Examples of further routes of exploration could be framing effects and reversibility, the effect of reference dependence over time, or the interaction between multiple cognitive biases (e.g. optimism bias and overconfidence) with reversibility in a privacy setting. The behavioral economics literature can also benefit from similar explorations contextualized outside of privacy decision making.

The growing literature surrounding the effects of privacy regulation can also benefit from the findings presented here. Regulation like GDPR is often broad, covering a sweeping array of privacy-related issues. Isolating specific tenets of said regulation will further lend to the insights surrounding its enactment. However, these tenets do not exist in a vacuum and likely interact, adding further complexity to their effects. Addressing the effects of privacy-regulation from both the perspective of individual changes and the interaction of such changes will allow for further development of the both the academic literature and policy discussions. Possible examples could include the interaction between data security requirements and privacy by design or the effects of net neutrality (which classifies internet service providers as telecommunications services instead of information services, thus dividing privacy regulation enforcement between the FCC and the FTC[9]) on the right to be forgotten.

5.2 Practical and Policy Implications

Our findings also have significant implications for firms, policymakers, and consumers. With respect to firms, it is widely known the role they play in utilizing consumer's behavioral biases (Conti and Sobiesk 2010). Receiving consent for data tracking practices can have significant economic benefit for firms. Navigating the changing privacy landscape in the face of new regulation can prove challenging to those firms that rely heavily on data. Understanding the intricacies of the decision-making process, and the biases that influence it, can assist firms in

[9] https://www.govtech.com/policy/gao-report-the-net-neutrality-debate-complicates-data-privacy.html#:~:text=It%20defines%20%E2%80%9CInternet%20data%20privacy,locations%2C%20and%20travel%20routes.%E2%80%9D&text=The%20Trump%20administration's%20FCC%20then,with%20the%20FCC's%20privacy%20rules.

designing interfaces that are appropriately protective while still allowing for considerable rates of consent. Firms also will likely benefit from understanding the role that reversibility plays in consent elicitation. A common practice for firms is to avoid "ringing the alarm bells" when it comes to privacy (Goldfarb and Tucker 2011a). Given that reversibility and irreversibility do cue individual's as to the seriousness of the decision, this will likely "ring the bell" in a way that may be undesirable to firms.

Policymakers will also benefit from these findings. Primarily, we highlight the delicate balance between protectiveness and economic benefit that is influenced by changing regulation. Adapting an active choice structure in favor of a universal opt-in has a modest impact for consumer protectiveness while still allowing for the considerable level of consent that firms desire. Further, a more protective opt-out default may be desirable in situations in which giving consent allows for highly intrusive practices or grants access to sensitive data. However, when the decision is repetitive, the protectiveness of the opt-out default increases, striking less of an economic balance. Finally, making reversibility salient in combination with default opt-out choices provides extreme protectiveness with questionable utility. Understanding the various levels of protectiveness can assist policymakers in designing regulation that strikes a proper balance with respect to specific choice contexts.

Finally, our findings have important implications for consumers. Privacy decisions are constantly being presented to individuals and have significant consequences. Data tracking practices can become highly intrusive and impact consumers in ways that are often unbeknownst to them. Understanding one's own behavioral biases can assist consumers in overcoming them through more careful consideration of consent decisions. Learning to navigate changing choice architectures in light of privacy regulation can be confusing to consumers. A careful consideration of the benefits and drawbacks to various regulatory instantiations can prove essential to an individual's privacy decision making.

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7. Appendices

7.1 Appendix A – Exogeneity of Social Desirability Manipulation

7.1.1 A-1 – Effect of Choice Architecture with SDB Treatment

VARIABLES	(1) Log-In	(2) Log-In
Active Choice	-0.115***	-0.115***
	(0.0211)	(0.0213)
Opt-Out	-0.409***	-0.408***
	(0.0254)	(0.0256)
SDB Treatment	-0.00286	-0.00368
	(0.0123)	(0.0123)
Constant	0.921***	0.924***
	(0.0359)	(0.0544)
Context FE	Yes	Yes
Controls	No	Yes
Observations	1,526	1,526
R-squared	0.158	0.161

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.1.2 A-2 – Effect of Reversibility with SDB Treatment

VARIABLES	(1) Log-In	(2) Log-In
Active Choice	-0.120***	-0.117***
	(0.0377)	(0.0380)
Opt-Out	-0.338***	-0.334***
	(0.0435)	(0.0436)
Reversible	0.00118	0.00286
	(0.0286)	(0.0292)
Irreversible	0.00133	0.00213
	(0.0290)	(0.0290)
Active*Reversible	0.0173	0.0143
	(0.0518)	(0.0527)
Active*Irreversible	-0.00318	-0.00517
	(0.0524)	(0.0526)
Opt-Out*Reversible	-0.107*	-0.113*
	(0.0621)	(0.0625)
Opt-Out*Irreversible	-0.106*	-0.111*
	(0.0619)	(0.0619)
SDB Treatment	-0.00449	-0.00538
	(0.0123)	(0.0123)
Constant	0.924***	0.893***
	(0.0394)	(0.0608)
Context FE	Yes	Yes
Controls	No	Yes
Observations	1,526	1,526
R-squared	0.163	0.165

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.1.3 A-3 – Effect of Experience with SDB Treatment

	No Statement	No Statement	No Statement	No Statement	No Statement	No Statement	No Statement
	(Study 1)	(Study 2)	(Study 3)	(Study 1)	(Study 2)	(Study 3)	(Panel)
VARIABLES	Log-In	Log-In	Log-In	Log-In	Log-In	Log-In	Log-In
Active Choice	-0.120***	-0.143***	-0.120***	-0.115***	-0.135***	-0.115***	-0.108**
	(0.0379)	(0.0354)	(0.0379)	(0.0389)	(0.0363)	(0.0389)	(0.0445)
Opt-Out	-0.337***	-0.396***	-0.337***	-0.332***	-0.391***	-0.332***	-0.307***
	(0.0437)	(0.0421)	(0.0437)	(0.0444)	(0.0427)	(0.0444)	(0.0501)
Study Number							0.0178**
							(0.00835)
Active*Number							-0.00848
							(0.0116)
Opt-Out*Number							-0.0327**
							(0.0136)
SDB Treatment	-0.00814	-0.0102	-0.00814	-0.00716	-0.00673	-0.00716	-0.00931
	(0.0215)	(0.0213)	(0.0215)	(0.0219)	(0.0216)	(0.0219)	(0.0204)
Constant	0.938***	0.971***	0.938***	0.934***	1.072***	0.934***	0.882***
	(0.0435)	(0.0418)	(0.0435)	(0.0995)	(0.0936)	(0.0995)	(0.0885)
Context FE	No	No	No	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes	Yes	Yes
Observations	498	498	498	498	498	498	1,494
R-squared	0.113	0.156	0.113	0.120	0.170	0.120	
Number of IDs							498

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

	Reversible or	Reversible or	Reversible or	Reversible or	Reversible or	Reversible or	Reversible or

	Irreversible	Irreversible	Irreversible	Irreversible	Irreversible	Irreversible	Irreversible
	(Study 1)	(Study 2)	(Study 3)	(Study 1)	(Study 2)	(Study 3)	(Panel)
VARIABLES	Log-In	Log-In	Log-In	Log-In	Log-In	Log-In	Log-In
Active Choice	-0.113***	-0.119***	-0.113***	-0.114***	-0.120***	-0.114***	-0.115***
	(0.0254)	(0.0254)	(0.0254)	(0.0259)	(0.0258)	(0.0259)	(0.0272)
Opt-Out	-0.445***	-0.463***	-0.445***	-0.446***	-0.463***	-0.446***	-0.441***
	(0.0312)	(0.0311)	(0.0312)	(0.0315)	(0.0313)	(0.0315)	(0.0339)
Study Number							-0.00289
							(0.00390)
Active*Number							-0.00157
							(0.00586)
Opt-Out*Number							-0.00795
							(0.00837)
SDB Treatment	-0.00261	-0.00419	-0.00261	-0.00359	-0.00508	-0.00359	-0.00247
	(0.0149)	(0.0150)	(0.0149)	(0.0149)	(0.0150)	(0.0149)	(0.0145)
Constant	0.928***	0.934***	0.928***	0.910***	0.909***	0.910***	0.884***
	(0.0327)	(0.0331)	(0.0327)	(0.0731)	(0.0687)	(0.0731)	(0.0635)
Context FE	No	No	No	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes	Yes	Yes
Observations	1,028	1,028	1,028	1,028	1,028	1,028	3,084
R-squared	0.184	0.197	0.184	0.188	0.201	0.188	
Number of IDs							1,028

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.2 Appendix B – Study Questions

Each question had the following possible answers: Yes, No, Prefer Not to Answer

Question	**Study**
While in a relationship, have you ever flirted with somebody other than your partner?	Romance
Have you ever used a dating app for the sole purpose of engaging in sexual activity?	Romance
Have you ever encouraged someone to drink when you were trying to seduce them?	Romance
Have you ever cheated while in a relationship?	Romance
Have you ever refrained from dating someone because of their skin color?	Romance
Have you ever looked at pornographic material?	Sex
Have you ever had a one night stand?	Sex
Have you ever taken nude pictures of yourself or a partner?	Sex
Have you ever had sexual thoughts about a member of your same sex?	Sex
Have you ever showered with a partner?	Sex
Have you ever used drugs of any kind (e.g. weed, heroin, crack)?	Crime
Have you ever let a friend drive after you thought he or she had had too much to drink?	Crime
Have you ever made up a serious excuse, such as grave illness or death in the family, to get out of doing something?	Crime
Have you ever stolen anything worth more than $50?	Crime
Have you ever downloaded pirated content from the internet?	Crime

7.3 Appendix C – Exit Questions

Each question was answered using a likert scale with the following responses: Strongly Agree, Agree, Neither Agree nor Disagree, Disagree.

Question
I was concerned about my personal privacy when completing this study.
My responess could be used in a way that may harm me.
My responses are valuable to the researchers.
Maintaining the privacy of one's personal information is very important.
I trust the researchers with my responses.
I was comfortable signing into my research profile.
I was less honest when signed into my profile.
My decision to log in during one survey impacted my decision to log in for subsequent surveys.
I thought more about my decision each time I was asked to log in.
I am logged into my account most times that I use an online web service (Google, Amazon, YouTube, etc.).

7.4 Appendix D – Balance Check

7.4.1 D-1 – Group Means

Variable	**Opt-In**	**Active Choice**	**Opt-Out**	**No Statement**	**Reversible**	**Irreversible**
Age	34.4 years	33.8 years	34.1 years	33.7 years	34.1 years	34.5 years
White	69.5%	68.1%	67.6%	69.3%	66.8%	69.2%
Black	10.7%	11.1%	11.6%	11.2%	11.4%	10.8%
Other Race	19.7%	20.8%	20.8%	19.5%	21.8%	20.0%
Male	53.0%	48.6%	45.3%	48.6%	50.7%	48.0%
< Bachelor	38.7%	37.7%	37.8%	37.1%	38.1%	41.2%
Bachelor	41.5%	42.3%	40.2%	41.0%	41.8%	38.9%
Advanced Degree	19.7%	20.0%	22.0%	21.9%	20.0%	19.8%
Full-Time Employed	44.9%	40.3%	44.1%	40.2%	44.6%	44.5%

7.4.2 D-2 – Balance Across Default and Reversibility Conditions

Variable	**Opt-In vs. Active Choice**	**Opt-In vs. Opt-Out**	**No Statement vs. Reversible**	**No Statement vs. Irreversible**
Age	0.193	0.454	0.390	0.101
White	0.369	0.234	0.144	0.950
Black	0.723	0.420	0.897	0.688
Other Race	0.447	0.458	0.114	0.698
Male	**0.014**	**0.000**	0.250	0.733
< Bachelor	0.557	0.582	0.584	0.880
Bachelor	0.684	0.452	0.622	0.314
Advanced Degree	0.833	0.117	0.212	0.165
Full-Time Employed	**0.009**	0.639	**0.014**	**0.015**

7.4 Appendix E – Consideration of Experience with Reversibility and Irreversibility Separated

	Reversible	Reversible	Reversible	Reversible
	(Study 1)	(Study 2)	(Study 3)	(Panel)
VARIABLES	Log-In	Log-In	Log-In	Log-In
Active Choice	-0.0992***	-0.132***	-0.127***	-0.0935**
	(0.0375)	(0.0381)	(0.0387)	(0.0394)
Opt-Out	-0.441***	-0.460***	-0.448***	-0.438***
	(0.0453)	(0.0452)	(0.0455)	(0.0491)
Study Number				2.79e-05
				(0.00550)
Active*Number				-0.0123
				(0.00919)
Opt-Out*Number				-0.00617
				(0.0122)
Constant	0.866***	0.908***	0.822***	0.834***
	(0.0801)	(0.0770)	(0.0824)	(0.0784)
Controls	Yes	Yes	Yes	Yes
Context FE	Yes	Yes	Yes	Yes
Observations	509	509	509	1,527
R-squared	0.194	0.206	0.198	
Number of ID				509

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

	Irreversible	Irreversible	Irreversible	Irreversible
	(Study 1)	(Study 2)	(Study 3)	(Panel)
VARIABLES	login	login	login	login
Active Choice	-0.122***	-0.103***	-0.0999***	-0.129***
	(0.0360)	(0.0355)	(0.0364)	(0.0377)
Opt-Out	-0.446***	-0.461***	-0.467***	-0.440***
	(0.0446)	(0.0445)	(0.0449)	(0.0473)
Study Number				-0.00564
				(0.00553)
Active*Number				0.00851
				(0.00736)
Opt-Out*Number				-0.00970
				(0.0115)
Constant	0.958***	0.955***	0.827***	0.913***
	(0.0793)	(0.0746)	(0.0898)	(0.0754)
Controls	Yes	Yes	Yes	Yes
Context FE	Yes	Yes	Yes	Yes
Observations	519	519	519	1,557
R-squared	0.195	0.205	0.210	
Number of ID				519

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1