Too Much Choice: End-User Privacy Decisions in the Context of Choice Proliferation

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ABSTRACT

Choice proliferation, a research stream in psychology, studies adverse effects of human decision-making as the number of options to choose from increases. We test if these effects can be elicited in a privacy context. Decision field theory suggests two factors that potentially affect end-users' reflection of disclosure decisions: (1) choice amount, which we test by changing the number of checkboxes in a privacy settings dialog; and (2) choice structure, tested by varying the sensitivity of personal data items which are jointly controlled by each checkbox. We test both factors in a quantitative 2×2 between-subject experiment with stimuli calibrated in a pre-study with 60 respondents. In the main experiment, 112 German-speaking university students were asked to enter personal data into an ostensible business networking website and decide if and with whom it should be shared. Using an established item battery, we find that participants who are confronted with a larger amount of privacy options subsequently report more negative feelings, experience more regret, and are less satisfied with the choices made. We observe a similar tendency, albeit weaker and statistically insignificant in our small sample, for the complexity of the choice structure if the number of options remains constant.

Categories and Subject Descriptors

K.4.1 [**Computers and Society**]: Public Policy Issues, Privacy

General Terms

Human Factors

Keywords

Privacy, Choice Proliferation, Experiment

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1. INTRODUCTION

Proliferation of choice is characteristic for post-industrial societies. It can refer to the number of decisions consumers are asked to make everyday and the number of alternatives to choose from for each decision. Choice proliferation is arguably driven by competition, product and service differentiation, technology-enabled mass customization, and the positive psychological effects inherent to choice [47].

Robust empirical evidence suggests that the provision of choice increases intrinsic motivation, perceived control, and life satisfaction [6]. Past decisions are also reflected on an psychological level where they may cause positive emotional states like satisfaction, happiness; but also negative states like regret, dissatisfaction, and indisposition [36]. A research stream in psychology believes that positive and negative emotional states in a decision-making process are determined by the amount of available options [51, 29]. Moreover, researchers in this field suspect that the accumulation of decision-making tasks is a reason for various negative psychological long-term effects including serious mental diseases, like clinical depression [53].

Choice also plays a key role in the domains of privacy and human-computer interaction. The positive notion of privacy as control over the collection and use of personal data [63, for example] suggests that more choice on information disclosure and sharing decisions is always better. This and the temptation to shift liability, encourages service providers to design more and more granular panels for privacy settings, thereby delegating more privacy decision to the end-user. For instance, Facebook has recently softened the default privacy settings for teenagers by adding more options to put the "decision to share in teens' hands" [33]. The number of end-user decisions in the privacy space is further inflated by legal obligations to inform consumers about the purpose of personal data collection and to request explicit consent [14].

Behavioral aspects of end-user privacy decisions are increasingly being studied. However, psychological side-effects of data disclosure and sharing decisions on individuals have rarely been addressed. This work tries to close this gap. It draws on the seminal choice proliferation literature and connects it with privacy research to explain why and how the amount of choice impacts end-users' privacy decisions and causes inherent psychological side-effects. We propose a decision-making model, based on elements of decision field theory, to derive testable choice scenarios (conditions) that are hypothesized to effect the users' decision-making process and its emotional reflection. In the main study (Study 2), we asked 112 participants to create a CV-like user profile in a guided process and let them subsequently decide which members of an ostensible business networking website they permit to view (parts of) their profile. The conditions modify the amount and structure of the information sharing decision. The key stimuli of the four conditions in our between-subject experimental design have been validated in a preceding quantitative study (Study 1).

By using scales established in consumer psychology and marketing research, we measure the participants' emotional reflections of the choice process. Our results are twofold: first, we show that an increase in choice amount correlates with more negative feelings towards past decisions; second, we identify behavioral attributes that may explain individual differences in the effect size.

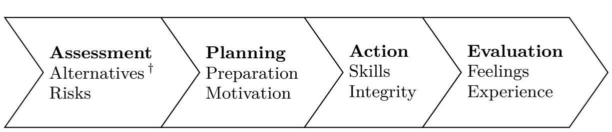
The remainder of this paper is organized as follows. Section 2 develops a theoretical framework. Sections 3 presents research questions and the empirical approach. The prestudy and the main experiment are reported in Sections 4 and 5, respectively. Section 6 discusses limitations and the final Section 7 summarizes and concludes with an outlook.

2. THEORETICAL BACKGROUND

Developing robust hypotheses on the relation between the amount of personal data sharing options and emotional reflections of the decision requires some solid theory. In this section, we adapt a general model of human decision-making from behavioral sciences to the specific domain of information privacy and, where appropriate, establish relations to prior experimental research of end-user privacy behavior.

2.1 Models of Human Decision-Making

There exist multiple psychological and cognitive frameworks that model conscious, rational or partly rational decision-making processes. The *Rubicon model*[1], for instance, describes a decision as a four-step process [28]. Figure 1 shows an adapted version. According to the model, a decision process starts with the assessment phase. The individual deliberates between possible alternatives by considering past experiences, knowledge, perceived risks, and valences. In the subsequent planning phase, necessary preconditions for the required actions are collected and elaborated. If the preferred alternative is selected and the necessary preparation is completed, the decision is translated into a sequence of actions. A decision-making process closes with an evaluation. The experience made and the fulfillment of intentions are reflected. The evaluation results are memorized as feelings (regret, satisfaction, etc.) and knowledge. They can be recalled for subsequent decisions.



† Structure and amount (our experimental factors)

Figure 1: Adapted version of the "Rubicon model" of action phases, cf. [28].

[1]There are various other famous choice models, like the preference trees [61] or elimination by aspects [60].

The assessment phase is an essential step in the decision-making process and there are various models that describe this phase in more detail. One of them is the *decision field theory* (DFT) [13]. DFT is a cognitive stochastic decision-making model which describes the process of deliberating between choice alternatives over time. The model assigns a payoff function to each alternative and explicitly assumes that humans accumulate the valence of each alternative over time. The preferred option can change various times during the accumulation process. This is captured in the model by letting payoffs fluctuate along stochastic processes. At any given point in time, the preferred alternative is the one with the highest accumulated payoff. The theory defines three thresholds, any of which, if exceeded, causes a termination of the decision process.

(1) The *decision boundary* defines the minimum amount of accumulated payoff required by an alternative to be considered as the final, most preferable outcome.

(2) The *time threshold* sets a maximum time for the decision process.

(3) The *preference change threshold* defines the maximum number of preference changes.

Upon termination, the decision maker selects the then preferred option or defers the decision. Decisions not terminated by the decision boundary amplify possible negative reflections of the decision process [30].

The frequency of preference changes and the time needed to make a decision are determined by the amount and distribution of the available alternatives. Concepts useful to model the size and the structure of choice alternatives are *density* and *entropy* [30, 22]. The terms originate from mathematics and information theory and were adopted in consumer psychology and marketing research to describe product assortments as inputs to a decision process. ("Options" and "products" are synonyms for the original term "alternatives" in the Rubicon model.) According to the density model, products are points in a high-dimensional attribute space. In a dense structure, the attribute values of each option lie closely together. A scattered structure is characterized by an increased number of extreme values and a larger distance between the attribute values of each option. While density requires numeric attribute values, entropy is applicable to numerical and categorial attribute values alike. It is calculated per attribute using Shannon's theory [54]. For a fixed number of options, an increase in the number of attribute values leads to a higher entropy.

The effectiveness of decision-making and in particular the assessment phase is determined by the decision strategy pursued. The set of strategies individuals apply to solve the same decision problem can be completely heterogeneous in many aspects [43, 24]. Each strategy implies a different configuration of the decision boundaries [17, 30]. A person who tries to optimize the benefit of the decision outcome, from now on called *optimizer*, sets a higher decision boundary and accepts more changes in preferences and more time to reach this boundary than a person who is not very interested in the decision quality, in the following called *satisficer* [55]. Assuming the same cognitive capabilities for both types of decision makers, an optimizer needs more resources than a satisficer. With limited resources it becomes harder to reach the decision boundary if the frequency of preference changes is high or time is scarce.

We conclude from this model: first, more options require a decision maker to assess more information, which requires more time and resources; second, if the option structure is dense or has high entropy, the number of preference changes is higher than in the case of a scattered option structure. That's because extreme non-fitting options can be easily sorted out at the beginning of the assessment phase. Both features affect optimizers more than satisficers.

2.2 Mechanisms of Choice Proliferation

Choice proliferation subsumes the increasing number of decisions and the growing number of available alternatives in the assessment phase of a decision process. Choice proliferation is studied by researchers originating from psychology, marketing, consumer research [50], and occasionally computer science [41]. As a result, there is no unified terminology and many terms exist to emphasize the negative consequences of choice proliferation, such as "tyranny of too much choice", "choice overload", or the "too much choice" (TMC) effect. We use the latter acronym to refer to the phenomenon.

On the upside, one should not forget that more choice primarily goes along with more freedom and autonomy [23]. It allows people to fulfill their individual needs and express their preferred way of living [48]. Choice further enables the exercise of control over the environment and prevents people from feeling helpless [15, 35, 46]. The benefits of having choice are therefore essential for human well-being.

On the downside, as indicated by the decision-making models, an increase in choice amount requires a decision maker to process more information and make more trade-offs. It increases the frequency of preference changes and time needed. As a consequence, individuals might fail to reach a decision boundary. Furthermore, more options imply more parameters to handle in order to maximize the decision output. This raises the decision boundary while the resources remain fixed. Both effects may trigger negative reflections of the decision-making process [51]. Researchers have two explanations for this link: first, the amount of options might exceed the cognitive capabilities of maintaining control, which provokes helplessness [53]. Second, more choice fuels the expectations to find the perfect satisfaction of needs, which, if not met, leads to the experience of regret, dissatisfaction, and disenchantment [8].

A general assumption of TMC studies is that effects triggered in the assessment phase materialize in the evaluation phase of a decision process (cf. Fig. 1). For example, in the domain of marketing, the amount of options, as part of the assessment phase, has a strong impact on the subsequent planing and action phase, i. e., consumers' purchase behavior [56]. Iyengar and Lepper's "jam study" [29] is generally considered as seminal for this field. They placed a tasting booth for different jams in a supermarket. All jams were of the same brand and could be purchased in the store. Customers in the control group of the between-subject experimental design were invited to sample no more than two jams from an array of six different flavors. Customers in the experimental group were allowed to sample two jams among 24 different flavors. The tasting booth which offered a larger amount of options attracted more people than the smaller one. But, customers in the control group were considerably more likely to purchase the product than customers of the experimental group. The researchers relate the unwillingness to purchase to choice deferral, which is believed to be an indicator for the TMC effect.

More than 40 follow-up studies provide empirical evidence on the TMC effect (see [50] for a survey). The dominant approach to simulate choice and its proliferation is to ask human subjects to choose one object out of a set of comparable options. The size of the set is varied between experimental conditions. Studies that successfully reveal the choice overload effect find a correlation between negative psychological effects (regret, dissatisfaction), measured with standardized instruments, and the amount of options. More recent research includes additional factors as control variables, such as time or the option structure. Apparently, not only the amount of options, but the overall complexity of the decision problem including option structure [22], time [27], etc. causes the TMC effect.

2.3 Choice and Privacy

Privacy is a multi-faceted concept and there is no universal consensus on its dimensions [57]. However, most scholars agree that privacy never implies absolute protection and emphasize the freedom of the individual to give up some privacy, for example by overriding safe defaults. Exercising this option implies choice, which raises the question on how this choice should be presented to end-users.

The term "choice architecture" has been coined by Thaler and Sunstein [59], who illustrate that the way how choice is presented can profoundly impact decision outcomes. In the context of privacy research, the term is used to describe the visual and logical presentation and composition of options that allow individuals to manage privacy-related tasks [19]. For example, the distinction between opt-in and opt-out policies [11] or the framing of consent dialogs [10] can be interpreted as instances of choice architecture. While privacy activists voice concerns about the inherent possibility of manipulation towards laxer sharing of personal data, empirical privacy research suggests that choice architecture can also be leveraged to nudge (i. e., manipulate) consumer behavior in the opposite direction, or at least to reach more conscious and thus fairer privacy decisions [2, 7].

There is a small but growing body of literature discussing the preservation of privacy under psychological constraints, comparable to the proliferation of choice. For instance, Böhme and Grossklags [9] comment on the trend to delegate all kinds of security decisions (security warnings, end-user license agreements, privacy notices and consent forms) from vendors to end-users. Since human decision capacity is scarce, only the most important decisions should be handled by the end-users. But individual vendors have little incentive to unilaterally suppress less important decision requests, such as take-it-or-leave-it decisions at install time, leading to habituated responses (clicking dialogs away) and a discrepancy between ostensible and actual control. Brandimarte et al. [12] analyze what they call *control paradox of personal information* empirically: If users have more control over the flow of personal data, they tend to disclose more sensitive information. Apparently, the perceived increase in control outweighs concerns regarding the subsequent access and usage of personal information. Other researchers have experimented with different granularity of privacy control options in a mobile location sharing scenario [32, 58]. All

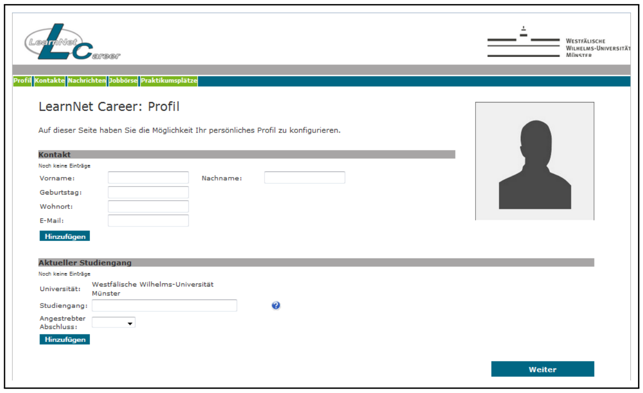


Figure 2: Profile page of the business networking website. (Original screenshot from Study 2)

studies demonstrate in a data disclosure context that the outcome of a decision process depends on the structure of the available options. Our research differs in that the dependent variable is not the decision outcome (disclosure), but, in line with the TMC tradition, psychological reflections in the evaluation phase.

What remains is to reason about the experimental factor (choice amount) in a privacy context. Practical online privacy management builds on a number of mechanisms that allow individuals to actively manage data disclosure and access permissions: consent dialogs [10], privacy settings [26], or the data entry fields where the actual disclosure happens [44]. A very general way of looking at data usage permissions is the access control matrix (ACM) [34]. An ACM consists of a set of objects O (originally: system resources, files, processes), protected by access rights, and a set of subjects S (users or processes operating on their behalf), who can be granted those rights. In a privacy context, the resource correspond to personal data items and the subjects can be recipients or purposes. The amount of options is determined by the number of O (objects) and S (subjects). An $O \times S$ matrix requires the user to decide $O \times S$ times whether a given piece of information should be shared with the given subject or not.

3. EMPIRICAL APPROACH

Our general goal is to empirically investigate possible TMC effects for end-user privacy decisions. To this end, we derive specific research questions from the presented theory (Sect. 3.1), develop a plausible scenario where TMC effects may appear (Sect. 3.2) and can be measured with specifically tailored stimuli (Sect. 3.3) in a between-subject experimental design. We run a pre-study to calibrate the stimuli (Study 1, Sect. 4) and collect empirical evidence to answer the research questions in the main study (Study 2, Sect. 5).

3.1 Research Questions

The designated approach is to design an ACM for personal data sharing permissions, as introduced in Section 2.3, to simulate different disclosure decision scenarios. An ACM can be manipulated pretty flexibly to adjust the amount of choice ($O \times S$). We formulate our first research question (RQ) accordingly:

Research Question 1. *How does the number of options presented in an access control matrix for personal data sharing permissions affect the attitudes towards the decisions in the reflection phase?*

As outlined in Section 2, individuals reflect a decision more negatively not only for the increased choice amount, but also for the inherent complexity of the decision. We understand the complexity as a latent factor moderated by the structure of the presented options. In the context of privacy, a suitable actuator for the decision complexity—independent of the number of options—is the perceived sensitivity of data items bundled together as objects in the ACM. More specifically, we assume persons who must decide if a set of data items with similar sensitivity should be disclosed or not face a less complex decision than those who are presented with more heterogeneous sets. Therefore:

Research Question 2. *How does the complexity of a data sharing decision, represented by the grouping of items of more or less similar sensitivity, affect the attitudes towards the decisions in the reflection phase?*

The attitude towards the decision in RQ 1 and RQ 2 is operationalized by two measurement scales. The TMC scale combines established items which measure emotional effects (satisfaction, regret, feeling overwhelmed) as an indicator for having too much choice. Second, the combined items of our perceived comfort, risk and trustworthiness (PCRT) scale are designed to capture how the participants feel while interacting with a website, specifically. Clearly, the PCRT scale is more exploratory. It has not been used in TMC studies before.

Also on the exploratory side and as a follow-up question, we are interested to which extent character traits may cause people to be more or less prone to the TMC effect.

Research Question 3. *Can we find individual differences moderating the TMC effect in privacy decisions?*

In particular, we are interested in how privacy concerns (PC scale) and the participants' generally pursued decision strategy (MAX scale) affect ratings on the TMC and PCRT scales. The PC scale combines different established items used in privacy research. With the help of the MAX scale, originally developed by Schwartz et al. in [52], we can classify participants into satisficers or optimizers. (All scales are further described in Sect. 5.1.)

3.2 Scenario

The main difficulty of adopting TMC studies from the domain of consumer and marketing research to privacy is that attributes of data sharing options are much more abstract than properties of tangible goods. For classical goods, consumers have formed expectations, often based on experience, and they have a clear and largely homogenous idea of the value. By contrast, the costs and benefits of privacy options are rarely monetary and therefore less salient and hard to assess and compare. In general, privacy preferences, attitudes and behavior alike, differ substantially between individuals [3]. Simulating an information disclosure situation which is perceived as an actual decision process more or less uniformly by all participants of an experimental study, while maintaining external validity and satisfying practical and ethical constraints, turned out to be quite challenging.

We follow [39] and choose a job market scenario for our TMC experiment. We created a business networking website inspired by existing services like LinkedIn or Xing[2]. Unlike popular open networks, our service was described as exclusive offer to students and graduates of one large German university who can use the platform to get in touch with potential employers. As a special feature, the service might authentically signal grades and recommendations from the university to the job market. To support this cover story, we called the service "Learnnet Career", alluding to the name of the Moodle-based e-learning and course management platform of the university. Study participants were invited to serve as beta-testers of a prototype of the new platform. They were asked to log in with their campus account and complete a CV-like profile (see Fig. 2). Tooltip examples next to the entry dialogs as well as the assurance that temporary information can be corrected and completed with details later (e. g., exact dates), helped to reduce the barriers of entering valid information. Data available in the campus directory was offered for direct import into the profile.

3.3 Experimental Conditions

After completion of the profile, participants were asked to configure data sharing permissions with an ACM. All defaults were set to not sharing and the participants had to opt in by checking the corresponding boxes. We varied the size and the structure of the ACM between four experimental conditions to elicit the TMC effect.

Privacy Settings			
Profile Information (Objects)	Members (Subjects)		
	Fellow Students	All Employers	All network members
Name Surname Age	☐	☐	☐
Job Experience Education	☐	☐	☐
Relationship status Political Interests	☐	☐	☐

(a) Homogeneous object structure.

Privacy Settings			
Profile Information (Objects)	Members (Subjects)		
	Fellow Students	All Employers	All network members
Name Surname Relationship status	☐	☐	☐
Job Experience Age	☐	☐	☐
Education Political Interests	☐	☐	☐

(b) Heterogeneous object structure.

Figure 3: Modifying the object structure in an ACM of a business networking website: red highlights mark differences in the similarity of sensitivity levels. Actual stimuli were shown without highlights. The white boxes symbolize checkboxes that can be clicked in order to share the personal data items.

To vary the choice amount, we configure a small (6 checkboxes) and a large (42) array of options. To further modify the decision complexity independent of the choice amount, we vary the object structure between a homogeneous and heterogenous version (see Fig. 3). Both variables are combined in a 2×2 between-subject experimental design. Table 1 lists all four conditions used in Study 2. Two screenshots of the ACMs in the actual experiment, Figure 10 for Condition 0 and Figure 11 for Condition 3, are provided in Appendix E (translated to English for this presentation).

[2]See www.linkedin.com, www.xing.com

Condition	Choice amount	Object structure	Decision complexity
0 (control group)	small	homogenous	
1	small	heterogeneous	
2	large	homogenous	
3	large	heterogeneous	

Table 1: Overview of experimental conditions

3.4 Hypotheses

In Sections 2 and 3.1 we have identified the option structure as a moderator of choice complexity. As indicated in Table 1, we expect that an increase in the choice amount amplifies this complexity. The resulting partial order lets us derive four hypotheses:

H1 Participants assigned to Condition 2 report a higher score on the TMC scale than participants assigned to Condition 0.

H2 Participants assigned to Condition 3 report a higher score on the TMC scale than participants assigned to Condition 1.

H3 Participants assigned to Condition 3 report a higher score on the TMC scale than participants assigned to Condition 2.

H4 Participants assigned to Condition 1 report a higher score on the TMC scale than participants assigned to Condition 0.

We refrain from formulating hypotheses on the effects on other measurements, like the PCRT scale, because this is beyond the scope of our decision-making model. Nevertheless, apart from the validation of hypotheses, we strive for an exploration of other, so far unexplained and less salient relations between the proposed measurements, conditions, and the TMC scale.

As we cannot rule out that the types of data recipients might affect the complexity of the disclosure decision, we are interested in the perceived trustworthiness of the subjects presented in the ACM. For instance, if all presented subjects are perceived as very trustworthy, the overall decision complexity might be very low irrespective of choice amount or object structure. A similar argument can be made if all items are perceived as either highly sensitive or not sensitive at all. Therefore, we deem it necessary to control these parameters. Since we cannot measure this information during the actual experiment, we carried out a pre-study (Study 1) to collect empirical data on contextual experience, as well as perceived sensitivity and trustworthiness of the objects and subjects in the ACM, respectively.[3]

[3]A comparable methodology is used in [37] and [45]

3.5 Recruitment and Ethical Aspects

Both studies were carried out online. Participants were recruited on a voluntary basis from a German-speaking university campus population, typically via personal invitation by the researchers in lecture halls of a variety of subjects and through word of mouth and social media. No tangible incentives were given and all instruments were compliant with German data protection law. Every participant was reminded to be part of an online study and that all personal data, including survey responses and profile information, will be stored on university-hosted servers.

Regarding ethical aspects, Study 1 is a typical opinion survey that does not involve deception nor touch any overly sensitive topic. Study 2 requires more careful consideration because the experiment was explicitly framed as an usability study of a business networking website, which was claimed to be currently developed by the university. Although the website adopted the corporate design of the university, it intentionally had a salient prototype-like appearance, i. e., most parts of the site were marked as "work in progress" or disabled. The candidates were told that by participating in this study they support the university in improving the usability of the planned service. It was further mentioned that they can share their profile with other participating members including potential employers. To minimize unfulfilled expectations, we did not name any company and further emphasized that the primary function of the network is to get in touch with potential employers and not to serve as a job search tool. In fact, the university already offers comparable services so that the website represents just another communication channel. In line with our expectations, and verified in Study 1, few participants reported to be actively looking for a job. Rather, they were interested in being contacted by local employers in general.

In the debriefing phase of Study 2, we informed the participants that this study was neither a usability study nor a real business networking website. We further mentioned that the purpose of this study was to test different layouts of privacy settings in business networking websites. We also asked our participants for honest comments after the debriefing and we have not received any expressions of disappointment. We further emphasized that all personal data except the survey responses will be deleted immediately.

Note that in Germany, it is primarily the responsibility of the individual researcher to ensure that a planned experiment does not violate research ethics, which are taught at length in many classes. IRBs for this kind of research are not very common. Nevertheless, we sought advice from experienced international researchers whom we met in the context of a summer school. None of them voiced concerns after we presented our empirical approach. Both studies also went through multiple (i. e., at least 20 for Study 2) iterative face-to-face pretests before the actual fieldwork.

4. STUDY 1

The purpose of Study 1 is to calibrate the stimuli for the conditions presented in Section 3.3 and to explore the contextual experience of our population with the scenario. We therefore asked the participants to report if they "never heard" (0), "heard" (1), or "are members" (2) of a business networking website. This *membership indicator* is used as a grouping variable to examine if the answers are invariant to contextual experience. The complete set of items used to measure contextual knowledge and motivations is listed in Table 9 in Appendix C. The main part of the survey asked the participants to imagine the role of a user of a business networking website. We provided additional background on how these networks usually work and what might be potential benefits for subscribers. We asked the participants to rate how comfortable they would be with sharing personal data items on their network profile. We use a 7-point *sensitivity scale* semantically anchored from "very uncomfortable" (1) to "very comfortable" (7) to record the responses. To reduce drop-outs or habituated responses, we divided the personal data items into two groups and distributed them over two survey pages. The order of the personal data items was randomized per subject to attenuate response order effects and to identify inconsistent answers. The *trust scale* asked the participants to rate the trustworthiness of other network members which will appear as subjects (S) in the ACM of the main study. Responses were collected on a 7-point scale, semantically anchored from "not trustworthy at all" (1) to "completely trustworthy" (7). The survey closed with questions on general privacy concerns (adopted from [56, 20]).

4.1 Results

We recruited 60 German-speaking participants and excluded the responses of 6 subjects because they failed to answer several items and revealed inconsistent response patterns. The remaining 54 participants were mainly students (90%, undergraduate and graduate), 25 female and 29 male, with an average age of 24.5 years (range: 18–33).

4.1.1 Contextual Experience

All participants were registered users of a mainstream social networking service and reported to use the service multiples times per week (75% multiple times per day). By contrast, only 29.8% reported to be active members of business networking websites. 25 of the remaining 40 participants (62.5%) have at least heard about such services. A minority of the participants (26.3%) reported to be on active job search, however, 86% answered to be interested in job offers by potential employers. Besides a moderate correlation between age and membership in a business networking website, we could not identify any demographic predictor for context-related items.

4.1.2 Sensitivity and Trustworthiness

In total we ranked 27 different personal data items, listed in Table 7, and 9 subjects, listed in 6 (both Appendix A). All items and subjects have been derived from real world instances of social or business networking websites. A set of test variables (items 25–27, e. g., alcohol consumption) was used to identify participants who did not actively process each option and picked elusive rating scores. The descriptive statistics show that for almost all data items, the full range of rating scores was used. A Shapiro–Wilk test revealed that the rating results did not follow a normal distribution ($p < .001$ for all 27 items). Because of this and the varying group sizes, we computed a series of Kruskal–Wallis one-way analyses. We tried to identify personal data items that are sensitive to different contextual experiences. The tests indicate that there is no significant difference in the medians between the three different levels of the membership indicator. The Kruskal–Wallis test applied to the trustworthiness scale found significant differences within subject "colleagues" ($\chi^2(2, N = 54) = 6.246,\ p < .05$). Pairwise post-hoc comparisons indicate that the mean scores between the groups "never heard" ($M = 3.31$, $SD = 1.888$) and "member" (colleagues: $M = 5.24$, $SD = 1.200$) differ significantly. Therefore, we conclude that individual differences about the trustworthiness of colleagues prevail and therefore decided to remove this subject from the final study. The full set of results including descriptive statistics are reported in Table 6 for the trustworthiness scale and Table 7 for the sensitivity scale (Appendix A).

4.1.3 Clustering

To determine the heterogeneous object structure by grouping personal data items, we computed an inverted distance matrix and fed it to a hierarchical Ward clustering (z-score scaled, Euclidean distance). To determine the homogeneous object structure, a k-means clustering (z-score scaled) was used. We compared the silhouette coefficient and the sum of within-group variances to measure for the quality of the clustering output. Due to the high variance in the scores of the personal data items, the clustering result for the homogeneous groups was expected to be only of moderate quality, which was eventually confirmed by our measurements.

In total we tested solutions with $k = \{1, \ldots, 7\}$ clusters. The k-mean algorithm uses a randomly selected starting point for the clustering process, which also affects the clustering quality. As a remedy, we ran 250 clustering iterations for each k and used the best result as a benchmark. Finally, we used the $k = 5$ solution which is depicted in Figure 9 (Appendix A) to design the final conditions. For the sake of readability, we decided to split group 5 with 13 elements in two groups of 5 and 8 elements, to finally obtain 6 clusters. The accepted solution had a rather weak model quality, but was sufficient to derive clearly distinguishable objects structures, as depicted in Figure 4. Each bar in the figure represents the sums of within-group variances of the four conditions. In both cases the heterogeneous compositions have a stronger variance than either corresponding homogeneous configuration. The final composition of all four cluster results is listed in Table 7 (Appendix A).

4.2 Discussion

Study 1 has helped us to gain valuable insights in how the quantitative experiment should be designed. Both the sensitivity and the trustworthiness scale facilitated the creation of suitable and empirically grounded stimuli for the four conditions in the main experiment. The successful clustering of data collected with randomized item orders demonstrates that participants respond attentively. We interpret this as an indication of generally good data quality.

5. STUDY 2

Study 2 tries to answer our confirmatory and exploratory research questions (Sect. 3.1); the former by testing the hypotheses formulated in Section 3.4, the latter by additional statistical analyses and visualization. The design of Study 2 is more complex than Study 1. Therefore we devote specific subsections to the description of the measurements scales and control variables (Sect. 5.1) and the procedure (Sect. 5.2).

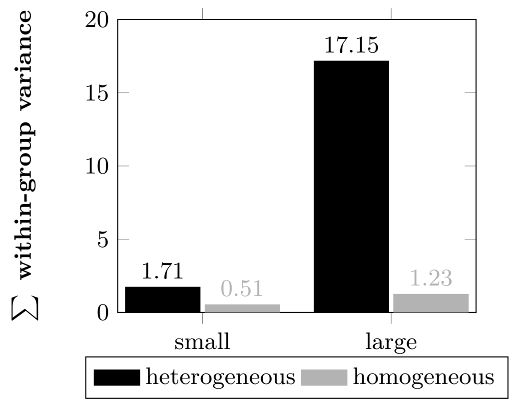


Figure 4: Empirical calibration of stimuli. Sum of the within-group variance for small (13) and large (24) choice conditions, broken down by the object structure. The heterogeneous object structure has higher within-group variance than the homogeneous object structure in both cases. (Study 1)

5.1 Measurement and Controls

Participants are asked to report their experiences, emotions, and opinions in entry and exit surveys. We use two latent dependent variables (DV) and two latent intervening variables (IV), all measured by summing up the responses to at least four indicator questions. This is a common procedure recommended to attenuate response errors on individual questions. To maintain internal consistency, we have eliminated items with a selectivity below 0.30 [21] (see Table 11 in Appendix D). A third intervening variable is collected from a single question with an ordinal scale. In addition to reactive measurements, we collect technical data about the participants' actual behavior as control variables.

5.1.1 Too Much Choice, TMC (DV)

Inspired by the items used in [41] and [50], we measure reported satisfaction, confidence, carefulness, and suitability with regard to the decision process and its outcome. The original question wordings were translated to German and adapted to the context of privacy settings. All responses are collected on 7-point semantically anchored scales. The TMC score is calculated as the sum of six items. It is our main dependent variable that measures immediate reflections of past disclosure decisions. A high TMC score indicates more negative feelings (dissatisfaction, frustration). The aggregated scale ranges from 6 (strong positive) to 42 (strong negative reflection). Post-hoc, this scale had "excellent" reliability as indicated by Cronbach's $\alpha = .922$.

Other published TMC studies either use rating scales of self-reported satisfaction with the decision process and its outcome, or a dichotomous indicator for the deferral of choice, offered by a symbolic no-choice option [16]. We leave deferral options in the privacy domain to future work.

5.1.2 Perceived Comfort, Risk & Trust, PCRT (DV)

Perceived comfort, risk, and trust are relevant factors in the assessment phase of a (disclosure) decision [18, 1]. We repurpose these factors as retrospective measurements to capture potential adverse impacts of general TMC effects. Persons who strongly regret a privacy decision might experience a deterioration of mood and project this negative

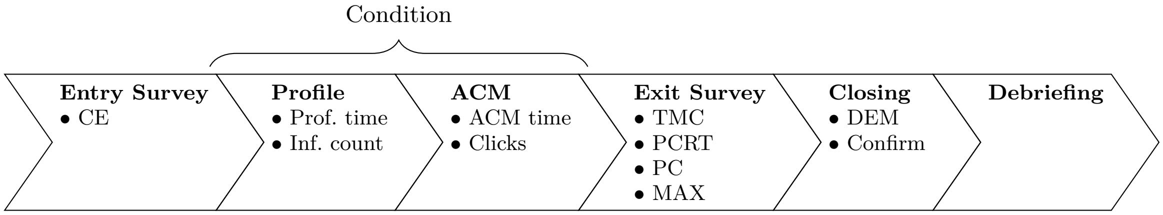


Figure 5: Process of the main experiment. Sequence of phases to be completed by the participants with associated measurement and control instruments. Conditions modify the stimuli presented in the Profile and the ACM phase. (Study 2)

feeling in a broader context than just the specific decision process. The aggregated scale ranges from 4 (strong positive perception of the website) to 20 (strong negative perception of the website). The PCRT scale had "acceptable" reliability as indicated by Cronbach's $\alpha = .693$. The lower reliability compared to the TMC scale is not surprising because the items were put together in an ad-hoc manner rather than by a sophisticated scaling procedure.

5.1.3 Privacy Concerns, PC (IV)

We use a 6-item scale with items adopted from [1, 20, 38] to measure general privacy concerns of the participants. We expect that more privacy-concerned participants produce higher PCRT scores in general. This means they assign a lower trustworthiness to the system and perceive more risks to their privacy. The scale ranges from 6 (strong privacy concerns) to 30 (no privacy concerns at all).

5.1.4 Maximizer, MAX (IV)

Schwartz et al. [52] developed a scale to test a decision makers' inclination of rather pursuing satisficing or optimizing (aka maximizing) strategies. We use 6 items out of the originally proposed 13 to build a scale where a higher value indicates a stronger tendency to maximize. The scale ranges from 6 (strong tendency to satisfice) to 54 (strong tendency to optimize).

5.1.5 Contextual Experience, CE (IV)

We chose to embed our experiment in a business networking website and could not expect that every participant is already familiar with such a service. Against the backdrop that researchers struggle to identify domain-specific expertise as a robust moderator of the TMC effect [49, 50], we decided to use the membership indicator along with other contextual experience questions from Study 1 as controls that allow for further interpretation of the results. Table 9 (Appendix C) reports the full list of questions including filter conditions.

5.1.6 Embedded Controls

The layout of the website mimicked the university's corporate design and the structure of its e-learning and course management platform. Unlike in Study 1, participants in Study 2 had to log-in with a valid university account. During the briefing phase, the participants were addressed with their real name, which we retrieved from the university directory.[4] We did this to reinforce the official character of the website. None of 20 pre-testers doubted that the website is an official university service.

During the experiment, we measured four behavioral control parameters to explain differences in the TMC results: time needed to complete the profile, time spent on the privacy settings, total number of clicks in the ACM, and the number of personal data items entered (excluding obvious nonsense, which we identify on the fly with basic natural language processing). We also queried the size of the browser window and whether scrollbars were displayed in order to control for potential influences of the visual presentation, in particular of the ACM, on the responses.

5.2 Procedure

Figure 5 visualizes the sequential process each participant in Study 2 went through. The second (profile) and third (ACM) phase were introduced by preceding task descriptions, which are reported in Table 8 (Appendix B). We kept the functionality of the website to a minimum in order to avoid distraction from the participants' main tasks. In the profile phase, participants of the small (large) conditions were asked to enter a minimum of 27 (40) types of information in a CV-style profile. Most information types could be entered multiple times (education, work experience). The profile setup was structured as a step-by-step tour through different input forms, asking for different types of information which are commonly used in online social and business networking websites. To overcome potential inhibitions and uncertainties, we provided a descriptive social norm by annotating each input field with a tooltip that provided examples for suitable input values. The layout for small and large conditions differed only by the number of information items that could be entered. The choice structure did not affect the stimulus of the profile phase.

Participants who completed their profile were forwarded to the ACM page, framed as "privacy settings" dialog. The size and structure of each group of personal data items (in rows) as well as the number of subjects (in columns) were determined by the randomly assigned condition (compare Sect. 3.3 for more details).

After adjusting the privacy settings, the participants were forwarded to the exit survey, which contained the items for the TMC, PCRT, PC, and MAX scales. As an icebreaker question, we asked the participants to rate the general usability of the website and the idea of providing such a service by the university. We used reverse-coded items to identify

[4] In line with our privacy policy, the name and account is bound to a session in memory only and not recorded in the research data. For the time of the fieldwork, we use a separate data structure to record hashes of account names for the purpose of detecting and preventing multiple participations by the same account holder.

participants with inconsistent reporting behavior.

In the closing phase, we reminded the participants that their profile will be stored independently of their survey responses and asked them to provide some additional demographic information (DEM). The experiment closed with a confirmation question asking if the responses were truthful enough and whether the record should therefore be included in the analysis or deleted (Confirm).

In the debriefing we informed the participants about the true purpose of the study and that their profile will be deleted for data protection (cf. Table 8 in Appendix B for the wording and Sect. 3.5 for ethical considerations). All participants had the opportunity to give us feedback in an open-ended question.

5.3 Results

We recruited 112 volunteers as participants. Data from thirteen participants were removed because they dropped out or entered obviously false information during steps 1 or 2 (entry survey, profile information), or dropped out in early stages of the exit survey. Recall that information disclosure was on a voluntary basis and no information type was mandatorily requested by the system. As a consequence, some participants entered only small fragments of information. Those participants tended to spend less time on the ACM than other participants in the same condition. To reduce the amount of noise in the data, we decided to remove all records of participants who entered less than 80% of the requested minimum 27 (40) information items. After imposing this restrictions, data from 81 subjects remains in the statistical analysis, with 19–22 cases per condition. The remaining 81 participants were all students (undergraduate and graduate combined), 40 female and 41 male, with an average age of 25.0 years (range: 18–31). Unless otherwise stated, we use ANOVA to test for differences in score means between conditions and Pearson's product moment coefficient to measure correlations between scales.

5.3.1 Main Effect

Figure 6 shows boxplots of the two dependent variables broken down by condition. Participants in the large choice conditions tend to report higher TMC scores than participants in the small choice conditions. Table 2 reports the results of pairwise one-way ANOVAs. The difference in TMC means is statistically significant ($p \leq .05$) in the hypothesized direction between Conditions 0 and 1 and highly significant ($p \leq 0.001$) between Conditions 1 and 3. **Hypotheses H1 and H2 are therefore supported. This contributes to the answer of RQ 1.** We also observe a tendency in line with our expectations for the effect caused by the object structure while the choice amount remains constant. However, the differences in means between Conditions 0 and 1 (small choice amount) as well as between Conditions 2 and 3 (large choice amount) are not statistically significant. **Therefore we reject hypotheses H3 and H4, which are both associated with RQ 2.** The object structure does not seem to raise the TMC score; or not strong enough to distinguish it from noise in our sample.

These results are echoed by the PCRT scale, though statistically less significant (but above the $p \leq .05$ threshold).

We find a positive but low correlation between the TMC and PCRT scale ($r(81) = .168, p > .05$), indicating that both scales measure different negative consequences of choice overload. Moreover, participants with higher privacy concerns (PC) perceive more risks, are less satisfied with the protection of their privacy (PCRT, $r(81) = -.274, p \leq .05$), and are less satisfied with their disclosure decisions (TMC, $r(81) = -.269, p \leq .05$) across all conditions. **This sheds initial light on RQ 3.**

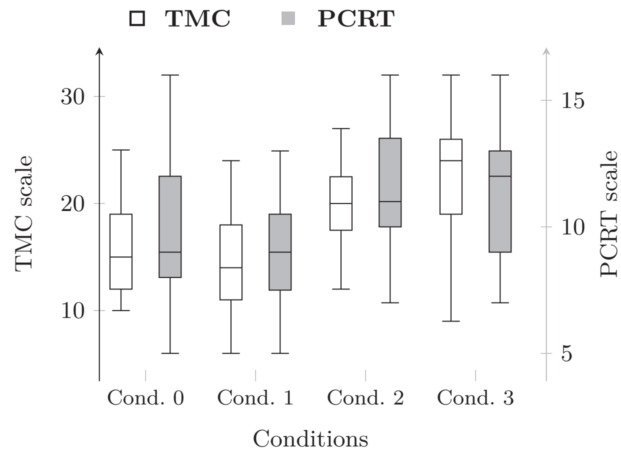


Figure 6: Boxplot of TMC (LHS) and PCRT (RHS) scores by condition. Higher scores for Conditions 2 and 3 indicate that more options negatively affect satisfaction (TMC) and trust (PCRT). (Study 2)

	Comparison	N	TMC	PCRT
H4	Condition 0 < Condition 1	39	.156	.534
H1	Condition 0 < Condition 2	39	4.256 *	5.535 *
	Condition 0 < Condition 3	42	14.344 ***	4.498 *
	Condition 1 < Condition 2	37	4.389 *	10.004 **
H2	Condition 1 < Condition 3	42	13.078 ***	8.561 **
H3	Condition 2 < Condition 3	40	3.206	.096

$^{*}p \leq 0.5$, $^{**}p \leq 0.01$,$^{***}p \leq 0.001$

Table 2: Statistical significance tests for differences between conditions in the TMC and PCRT scores. F-values of one-way between-subject ANOVAs, two-sided p-values for robustness. (Study 2)

To the best of our knowledge, this is the first empirical evidence that participants who are confronted with larger and more complex personal data disclosure decisions reflect the decision process more negatively in terms of satisfaction, regret, and feeling overwhelmed (i. e., higher scores on the TMC scale) than participants who face a small and less complex disclosure decision. Furthermore, we observe a noticeable negative effect of the large choice condition on the reported trustworthiness of the website and the perceived comfort when using it (higher scores on the PCRT scale). For completeness, Table 3 reports the first two moments for the two dependent variables broken down by condition and individual items.

In summary, our results consistently support a causal influence of choice amount on the evaluation phase of end-user privacy decisions. They also do not rule out the possibility that the choice structure has some impact on the reflection of a decision, but the amount of choice was more decisive in our setup. This is not very surprising, because the manipulation of the structure has more subtle effects and is thus harder to identify in small samples.

DV*	Cond. 0		Cond. 1		Cond. 2		Cond. 3	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
TMC	16.04	4.65	15.36	6.19	19.16	4.87	22.22	5.93
TMC1	2.86	1.15	2.58	1.07	3.21	.79	3.59	1.14
TMC2	2.71	1.15	2.68	1.16	3.32	.89	3.68	.99
TMC3	2.95	.97	2.63	1.26	3.11	.94	3.73	1.24
TMC4	2.52	.75	2.42	1.22	3.37	1.21	3.91	1.15
TMC5	2.67	1.02	2.57	1.22	2.79	.92	3.36	1.18
TMC6	2.33	.97	2.58	1.22	3.37	1.21	3.95	1.39
TMC7	4.10	1.34	3.16	1.39	3.11	1.24	3.36	1.59
PCRT	9.61	2.64	9.05	2.22	11.63	2.77	11.36	2.75
PCRT1	1.43	.51	1.42	.51	1.21	.42	1.50	.97
PCRT2	1.43	.60	1.63	.76	1.47	.77	1.77	.69
PCRT3	1.57	.51	1.42	.61	1.47	.70	1.68	.78
PCRT4	1.62	.59	1.37	.60	2.00	.68	1.73	.63
PCRT5	1.52	.81	1.42	.51	2.16	.96	2.05	.84
PCRT6	1.76	.77	1.74	.73	2.21	.86	2.14	.83

* Wording provided in Table 11

Table 3: Means and standard deviations of the complete TMC and PCRT item pool (no items excluded) broken down by condition. (Study 2)

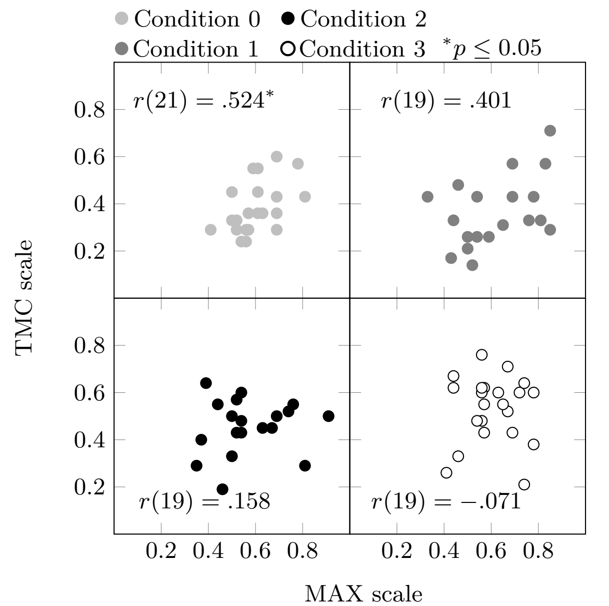


Figure 7: Scatterplots and Pearson product-moment correlation of normalized TMC and MAX scores. In conditions 0, 1, and 2 maximizers tend to be less satisfied with their choices made. (Study 2)

5.3.2 *Individual Differences in Decision Strategies*

Following [52], we compute a median split of the MAX scores to distinguish between statisficers and optimizers. We did this to ascertain that both characteristics are equally distributed over all conditions (cf. Table 4). We use the full scale score to test if the tendency to optimize affects the individual TMC score. We find a moderate correlation between the MAX and TMC scores in both small choice amount conditions (significant only for Condition 1, cf. Figure 7), but not for the large choice amount conditions. We conjecture that personal traits and habits influence the overall rating score more in simple decisions than in cases which require more systematic processing for the sheer size of the decision space. **This adds to a partial answer of RQ 3**, but more research is needed to fully understand the underlying mechanism.

5.3.3 *Demographics and Contextual Experience*

We find no significant differences in the demographics between conditions (cf. Table 4). This is reassuring because demographic attributes apparently do not cause differences in drop-out rates or reported scores. The distribution of the membership indicator over conditions groups is also reported in Table 4. We cannot find a sign of statistical dependence between the TMC score and the membership indicator, neither in total nor within conditions. The same holds for all other reported demographics. This is in line with our findings in Study 1, where neither contextual experience nor age or gender had a significant influence on other ratings.

5.3.4 *Embedded Controls*

We estimate a linear multiple regression model per group to capture the relation between the control mechanisms and the TMC score. Analyses across groups are out of the scope of this paper because groups are not directly comparable for some controls. The following parameters are included as predictors: the time spent on the privacy settings page (*privacy_time*), the total number of clicks in the ACM (*clicks*), the number of data sharing permissions (*total_shared*), and the number of personal data items entered in the profile (*answered_fields*). We are aware of potential multicollinearity issues. In particular, *clicks* and *total_shared* are closely associated. However, in all cases the variance inflation factor varied in the permissible range between 1 and 3 [40].

As indicated by the regression results shown in Table 5, the most stable predictor across all conditions is *clicks* followed by *total_shared* and the number of personal data items entered in the profile. All of them are positively associated with the TMC score. The time spent on the privacy settings page appears to be the weakest predictor and is correlated even negatively in one case. However, very few of the predictors differ significantly from zero. This may be partly due to the relatively high number of predictors compared to the sample size. In general, the models for the large condition groups explain a larger share of the variance in the TMC score. This corroborates the conjecture in Sect. 5.3.2 that the TMC score is dominated by the condition if the decision space is large, thereby displacing other factors that tend to have a smaller and more heterogeneous influence.

A series of product-moment correlations computed between the overall TMC scores and the four predictors identifies the number of clicks as strongest covariate ($r(81) = .614, p \leq .001$, see Figure 8 for a visualization).

5.4 Discussion

The results of Study 2 can be divided in results related to the experimental factors, which permit a causal interpretation, and results related to individual traits, which are self-reported and therefore prone to endogeneity issues.

The experiment revealed that a larger number of data sharing options causes significantly more negative emotional reactions in the evaluation phase of a decision process, as reported on established items of the TMC scale. The results confirm the hypothesized negative impact of choice proliferation on satisfaction, the experience of regret, and feel-

Condition	N	Gender (%)		Age		Decision strategy (%)		Membership indicator (%)		
		Female	Male	Mean	Max	Optimizer	Satisficer	Never Heard	Heard	Member
Condition 0	21	47.6	52.4	25.48	29	47.62	52.38	9.5	66.7	23.8
Condition 1	19	57.9	42.1	25.32	30	47.37	52.63	5.3	57.9	36.8
Condition 2	19	52.6	47.4	24.37	29	36.84	63.16	5.3	68.4	26.3
Condition 3	22	40.9	59.1	24.86	31	45.46	54.54	13.8	54.5	31.7
Total	81	49.8	50.2	25.01	31	44.32	55.68	8.5	61.8	29.7

Table 4: Demographics, decision strategy, and membership indicator by condition. (Study 2)

Regression	clicks		total_shared		privacy_time		answered_fields		Constant		Model	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t	Coef.	t	R^2 adj.	F
Condition 0	.953	1.056	3.323	1.130	−.144	−.532	.093	.191	4.254	.332	−.049	.766
Condition 1	2.017	1.539	3.113	1.098	.111	.457	.682	.851	−18.550	−.719	0.58	1.276
Condition 2	1.252*	2.249	.246	.453	.052	.284	.110	.354	−1.994	−.272	.487**	5.276
Condition 3	1.490**	2.992	.021	.019	.093	.614	.345	1.067	−10.589	−.796	.465**	5.569

$^*p \leq .05$, $^{**}p \leq 0.01$, $^{***}p \leq 0.001$

Table 5: Results of linear multiple regressions, one per condition. Dependent variable: TMC score. The number of clicks in the ACM and the total number of data sharing permissions are the strongest positive predictors of the TMC score. (Study 2)

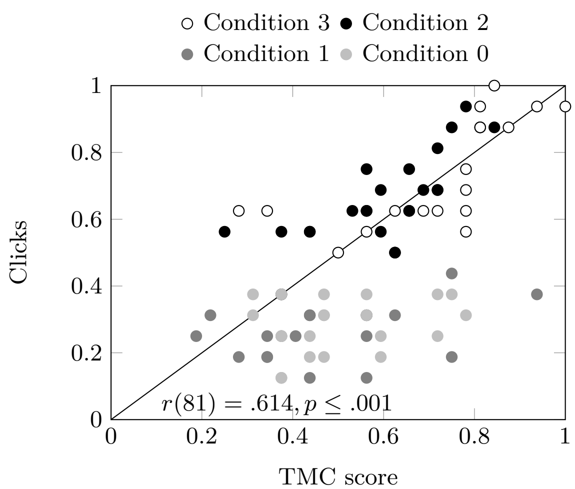


Figure 8: Scatterplot and Pearson product-moment correlation of normalized TMC scores and number of clicks. More clicks are associated with higher dissatisfaction with the choices made. (Study 2)

ings of being overwhelmed. The significantly higher PCRT scores in the conditions with large choice amount indicate that having more choice can also bias the perceived comfort, risk, and trustworthiness of the choice context (i. e. the website). The reported TMC and PCRT scores correlated positively, yet not significantly. This supports our assumption that the negative reflection of the decision, captured by the TMC score, spills over to a negative perception of the overall scenario. It remains the task of future research to investigate more into the causal links between the items perceived comfort, risk, and trustworthiness and the emotional reflection of the decision. To this end, it would be desirable to measure these latent factors with separate item batteries established in psychology. A combined scale, like our PCRT scale, is just a first exploratory step to test for a general relation with choice proliferation.

The analysis on individual differences in the TMC scores revealed mixed findings. Schwartz et al. [52] argue that people who tend to be optimizers suffer more from choice proliferation than satisficers. This theory is only partly confirmed by our results. Participants in the small conditions who reported comparable high TMC scores were more often classified as optimizers. On the other hand, this trait had almost no influence on the TMC scores in the large conditions. We encountered a similar pattern for the controls *clicks*, *total_shared* and *answered_fields*. All three predictors have a stronger influence on individual TMC scores if the choice amount was small. The sample in this work is too small to identify interactions between self-reported traits or control variables and the effect size of the experimental factors.

The hypothesized impact of the object structure on the TMC scale could not be confirmed in our experiment. Recall that our hypotheses are based on the assumption that people perceive choice as less difficult if the option structure is more similar. However, other researchers state that “introducing a small difference in an otherwise identical attribute can increase the perceived similarity of choice alternatives” [31]. This *similarity effect* might have suppressed the predicted effect of the heterogeneous object structure on choice complexity. Follow-up studies should therefore control for this factor, for example by using a quantitative procedure (clustering) to derive different option structures that are presented to human subjects for a rating of the perceived similarity.

6. LIMITATIONS

Although the specification of a decision model and the pre-study helped us to optimize our stimuli, we had to keep the scenario as realistic as possible to ensure external validity. This required compromises by relaxing controls in the experimental design.

For example, the participants were neither compelled to enter all information nor bound to a strict procedure. Hence, each participant experienced the study in a slightly different way. As a remedy, we removed records of participants who provided less than 80% of the requested information types. This leads to a more homogenous sample, but might have introduced a bias against more privacy-aware persons, as confirmed by inspecting the PC scores of the excluded records. In general, the well-known limitations of small convenience samples in a student population apply.

As a side effect of manipulating the choice amount, each condition came with visible changes in the profile and ACM. We considered manipulating the ACM only, but were afraid of confusing people by asking for data items that do not appear in the privacy settings. This may elicit feelings of limited control. Another difficulty is that extending the ACM involves adding objects (rows) and subjects (columns). This changes the object and subject structure of the entire decision. Such structural differences are hard to control and may be confounded with the effect of choice amount.

In the large choice conditions, the ACM dominated the layout and emphasized the complexity on a visual level. The same holds for all TMC studies, but in other contexts, the presence of a large choice amount often induces positive feelings at the first glance. We are concerned that this might not hold for our ACM matrix and the privacy domain in general. The TMC effect might have been stronger driven by the visual interpretation of the choice than in common consumer experiments. Although we stressed the benefits of sharing the data ("interesting potential employers might contact you"), this positive consequences may only materialize in the future and are therefore less salient. As a result, the participants might have perceived the task more as a burden instead of having the possibility of choosing among various different options, which all appear very attractive to them at present.

Another difference to conventional TMC studies is that psychology and marketing researchers present 1-out-of-n decisions. Strictly speaking, our privacy settings asked for n binary decisions, which are not necessarily independent. The overall decision complexity may grow disproportionally if the decision maker tries to strive for some sort of consistency. This may amplify the TMC effect in our setting.

Moreover, potential priming and response order effects of the exit survey phase cannot be excluded. In particular the questions asking for trust and risks, placed before and after the TMC question block, might have biased the participants' interpretation of the study.

Finally, the field of TMC research struggles to reproduce many published results and is still seeking for a comprehensive psychological understanding of the TMC effect in general [50]. Some authors even question the existence of a TMC effect in general and point out the lack of robustness against differences in cultures, context, an individual traits [50]. Therefore, our initial evidence in the privacy domain, obtained with a small and homogeneous sample, should be interpreted with caution and not used for policy advice unless the effect is replicated with independent data.

7. SUMMARY AND CONCLUSION

Our study provides initial empirical evidence of negative psychological effects triggered by the proliferation of choice in a privacy context. We use elements of decision field theory, consumer psychology and findings of TMC research in order to devise a model that illustrates selected aspects of a disclosure decision. We report the results of a comprehensive empirical study, a university-hosted business networking website, carried out to test our hypotheses with a quantitative 2×2 experiment. An adapted access control matrix served to simulate the disclosure decision with varying amount and structure of elements, depending on the randomly assigned condition. A pool of established items was used to derive four reliable scales: Too Much Choice (TMC), Perceived Comfort, Risk, and Trustworthiness (PCRT), Privacy Concerns (PC), and Maximizer (MAX).

We find that participants assigned to a large choice condition report to be less satisfied with their choices made, experience more regret, and are more overwhelmed by the decision process. Despite some limitations, we can successfully demonstrate that the number of privacy options presented to a user affects the (short-term) emotional reflection of the decision in the evaluation phase of a decision-making process. Additional exploratory analyses suggest that also the perceived comfort, risk, and trustworthiness of the decision context can be negatively affected by choice proliferation.

Applying this lens to privacy research breaks new ground. While research in psychology discerns the evaluation phase as an important phase of decision-making, privacy research so far seems to be focused on the assessment phase. Researchers try to understand why a decision maker assigns a higher value to the prospect "disclose" than "conceal". Also many interdisciplinary studies contribute to this research by incorporating psychological elements like trust, perceived risks and other concepts from behavioral economics. But even these psychological models are mostly applied to better understand the outcome and not the emotional consequences of decision making. Although there are a few studies which investigate why users regret the outcome of a disclosure decision, they do not capture the actual emotional reflection of the decision processes [62, 42] or use ad-hoc rather than established scales to measure the dependent variable [25]. This work demonstrates that in particular the investigation of a variety of emotional and psychological factors can provide new and valuable insights into end-users privacy decisions.

This work also contributes to the emerging literature which questions the policy trend of putting consumers in charge of controlling the dissemination of their personal data. Against the backdrop of a vastly growing data industry, this criticism appears counter-productive at first sight. However, consumers' privacy decisions are prone to manipulation by subtle changes of the decision context and the choice architecture. A concern commonly raised by privacy advocates is the possibility of strategic abuse of privacy choice architecture by data-intensive industries towards nudging consumers into disclosing personal information above a socially optimal level [19, 5, 4]. Our results suggest that if this implies that more and more disclosure and sharing decision are delegated to the consumer, this not only affects the users' sharing attitudes (identified in [12]) and unnecessarily consumes cognitive resources (as in [9]), but also has measurable emotional consequences in the short run. (We cannot say anything about longer-term effects.) This reinforces the recommendation to designers of privacy panels to not only focus on the layout and composition of privacy settings, but also follow choice minimizing principles and scrutinize the necessity of each additional option. It also reinforces ideas of automating end-user privacy decisions either by safe defaults or with appropriate standards and tool support.

8. ACKNOWLEDGEMENTS

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APPENDIX

A. EMPIRICAL RESULTS, STUDY 1

Type of network group	Descriptive Statistics[a)] M	SD	Kruskal-Wallis (omnibus)[b)] $\chi^2(2, N=54)$	p
Friends	5.60	1.405	3.038	.219
Fellow students	4.46	1.342	4.514	.105
Colleagues	4.35**	1.739	5.286	.008
Post-Hoc				
Heared, Member			2.396	.122
Never heared, Member			7.530	.006
Heared, Never heared			2.273	.132
Favorite employers	4.04	1.822	2.365	.307
Employers of a selected industry	3.92	1.702	.890	.641
Employment agency	3.46	1.756	2.674	.263
University employees	3.11	1.354	5.299	.071
All employees	3.02	1.596	.297	.862
All network members	1.81	1.150	2.210	.331

[a)] Aggregated, Trustworthiness scale (1) Not trustworthy at all , (7) Completely trustworthy
[b)] Grouping variable: membership indicator $^{**}p \leq 0.01$

Table 6: Check for invariance of the median (rank), grouped by membership indicator. $N = 54$. (Study 1)

#	Information Entity	Cluster allocation: Large Hom(Het)[c)]	Small Hom(Het)	Sensitivity[a)] M	SD	Kruskal-Wallis (omnibus)[b)] $\chi^2(2, N=54)$	p
1	Given name	1 (6)	1 (1)	5.72	1.45	4.219	.121
2	Family name	1 (4)	1 (1)	4.96	1.85	2.042	.360
3	Mobile number	6 (3)	-	1.79	1.46	4.424	.109
4	Age	1 (3)	1 (2)	5.62	1.39	.442	.802
5	Favorite food	5 (5)	-	3.00	2.17	.398	.819
6	Favorite TV show	5 (4)	-	2.30	1.78	.276	.871
7	Relationship status	4 (1)	-	1.98	1.52	.392	.822
8	Political interests	4 (3)	-	2.52	1.65	1.735	.420
9	Practiced sports	1 (3)	1 (2)	4.15	1.75	1.830	.400
10	Instant messenger number	6 (6)	-	2.35	1.62	2.507	.483
11	Gender	1 (2)	1 (1)	6.19	1.33	.168	.919
12	Favorite computer game	4 (2)	-	1.81	1.52	1.069	.586
13	Technical expertise	2 (1)	2 (2)	5.89	1.13	.892	.640
14	Job experience	2 (1)	2 (1)	4.81	1.84	5.722	.057
15	Current university grade point average	3 (3)	-	3.54	2.01	2.109	.348
16	Transcript of records (education)	3 (5)	-	3.48	1.80	3.430	.180
17	Education	2 (5)	2 (2)	5.31	1.60	1.969	.374
18	Social skills	2 (4)	2 (2)	5.75	1.26	4.167	.124
19	Language skills	2 (3)	2 (1)	5.89	1.21	.285	.252
20	Attended lectures (university)	2 (4)	2 (1)	4.99	1.70	1.315	.518
21	Selected university records	3 (2)	-	4.28	1.93	.174	.917
22	Received awards	2 (6)	2 (1)	5.24	1.62	4.725	.094
23	Topics of thesis	2 (3)	2 (2)	5.14	1.83	3.743	.154
24	Desired salary	3 (4)	-	3.26	1.68	1.678	.432
25	Medical records[d]	-	-	1.52	1.24	.889	.641
26	Favorite alcoholic drink[d]	-	-	1.40	1.03	2.149	.341
27	Frequency of alcohol consumption[d]	-	-	1.28	.818	.694	.707

[a)] Aggregated [b)] Grouping variable: membership indicator [c)] Hom = Homogeneous, Het = Heterogeneous [d] Removed test items.

Table 7: Clustered personal data items (column 1-2). Cluster results (column 3-4). Descriptive statistics for sensitivity scale (1) "Very uncomfortable" , (7) "Very comfortable" (column 5-6). Check for invariance of the median (rank), grouped by membership indicator (column 7-8).$N = 54$. (Study 1)

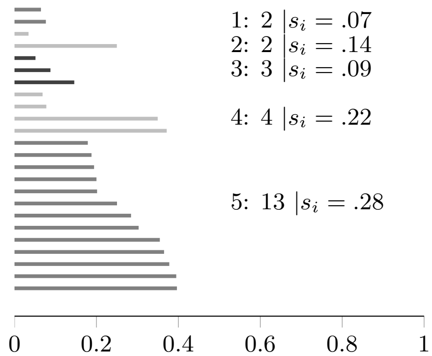

Figure 9: Average silhouette widths (x-axis: s_i) of 24 clustered information personal data items (y-axis). Best result of k-mean clustering with $k = 5$ and 250 iterations is displayed. Total average silhouette width $s_i/n = .22$. (Study 1)

B. TASK DESCRIPTION & DEBRIEFING, STUDY 2

Briefing prior to completion of CV-style profile[a)]
You can configure your user profile on the following pages. Try to keep distractions and interruptions up to a minimum while proceeding with this step! You have the chance to adjust your privacy settings after you have finished this step. Please try to answer all questions honestly and conscientiously. If you do not have particular information at hand, feel free to enter preliminary information which you have in mind. The information can be corrected afterwards. Please note that all answers and information are provided on a voluntary basis.
Briefing prior to managing privacy settings via the ACM
You can manage your privacy settings on the following page. The setting allows you to decide with whom you want to share all or parts of the information you entered. Your privacy is important to us! Take your time to find the privacy settings that you favor the most. To allow a person/group to view your information, you must tick the corresponding checkbox.
Debriefing
For privacy reasons, we will delete your entered profile information after you closed this site. The purpose of this study was to test different privacy settings in social/business networking websites. Please note that this study is not connected with any official university student service. If you have any questions concerning your privacy or are interested in the results of the study, you can contact us by email or leave your e-mail address here: [textfield].

[a)] Original text in German and screenshots available upon request.

Table 8: Task description and debriefing. (Study 2)

C. CONTEXTUAL BACKGROUND AND MOTIVATION, STUDY 1 & 2

Item ID	Wording[a)]
1	Are you actively searching for a new or another employer? ☐ Yes, ☐ No
2	Would you be interested if an employer approached you with a job offer? ☐ Yes, ☐ No
3	Are you a member of a business networking website like Xing or LinkedIn? ☐ Yes, ☐ No
3.1 if (3==no)	Have you ever heard of business networking websites like Xing or LinkedIn? ☐ Yes, ☐ No
3.2 if (3==yes)	Since when are you member of a business networking website? ☐ one month, ☐ one year, ☐ two years, ☐ three years or longer
3.3 if (3==yes)	How often are you using the business networking website ☐ multiple times per day, ☐ once a day, ☐ multiple times per week but less than once a day, ☐ once a week, ☐ less than once a week, ☐ more than once a month but less than once a week, ☐ less than once a week, ☐ I am a member but never used the site
4[b)]	Are you a member of an online social network like Facebook? ☐ Yes, ☐ No
4.1 if (4==no)	Have you ever heard of online social networks like Facebook? ☐ Yes, ☐ No
4.2 if (4==yes)	Since when are you a member of an online social network? ☐ one month, ☐ one year, ☐ two years, ☐ three years or longer
4.3 if (4==yes)	How often are you using the online social network? ☐ multiple times per day, ☐ once a day, ☐ multiple times per week but less than once a day, ☐ once a week, ☐ less than once a week, ☐ more than once a month but less than once a week, ☐ less than once a week, ☐ I am a member but never used the site

a) Original questions in German; wording and screenshots are available upon request.
b) Not used in Study 2.

Table 9: Contextual background and motivation of participants. (Study 1 & 2)

D. EXIT SURVEY AND RESULTS, STUDY 2

Item*	Anchors			
	Min (left)		Max (right)	
TMC1	Very unsatisfied	(1)	Very satisfied	(7)
TMC2	Very hard	(1)	Very easy	(7)
TMC3	No regret	(1)	Strong regret	(7)
TMC4	Not overwhelmed	(1)	Completely overwhelmed	(7)
TMC5	Not frustrating	(1)	Completely frustrating	(7)
TMC7	Completely insufficient	(1)	Completely sufficient	(7)
TMC6	Very unlikely	(1)	Very likely	(7)
PCRT1–6	Completely agree	(1)	Completely disagree	(5)
PC1–7	Completely agree	(1)	Completely disagree	(5)
MAX1–6	Completely disagree	(1)	Completely agree	(7)

* Wording and statistics are provided in Table 11. Original anchors in German.

Table 10: Left and right semantic anchor of all rating scales for the items in Table 11. (Study 2)

Scale	Item	Wording[c)]	Mean	SD	Item total correlation$^{a)}$
TMC $N = 81$ Mean = 18.30 Reliability[b)]: .922 Range: $[6, 42]$ Scale: 7-point semantic	TMC1 (RC)	How satisfied are you with the privacy settings you selected?	3.07	1.104	.803
	TMC2 (RC)	How easy was the selection of the appropriate privacy settings?	3.11	1.118	.806
	TMC3	Do you regret the privacy settings made and if so, how much?	3.12	1.166	.832
	TMC4	To which extent have you been overwhelmed by choosing the appropriate privacy settings?	3.07	1.243	.707
	TMC5	How frustrating was the selection of the correct privacy settings for you?	2.84	1.101	.702
	TMC6	Would you choose to correct the privacy settings if this option was available?	3.07	1.358	.724
	~~TMC7~~	Did you think the available privacy settings are sufficient or insufficient?	3.44	1.432	.249
PCRT $N = 81$ Mean = 6.59 Reliability: .693 Range: $[4, 20]$ Scale: 5-point Likert-type	~~PCRT1~~	This website appears to be very trustworthy.	1.40	.540	.275
	PCRT2	The risk of entering personal data into this website is low.	1.58	.705	.452
	PCRT3	I have the feeling that the personal data I entered are sufficiently protected.	1.54	.672	.449
	PCRT4	I would not mind using this website again.	1.68	1.790	.591
	PCRT5	I felt comfortable using this site.	1.79	.847	.489
	~~PCRT6~~	I was confident at any time that I have full control over the use of my personal data.	1.96	.813	.265
PC $N = 81$ Mean = 11.81 Reliability: .769 Range :$[6, 30]$ Scale: 5-point Likert-type	PC1	I am annoyed by companies who ask for my personal data.	1.96	.749	.553
	PC2	I take care not to give my personal data to Internet companies.	2.00	.758	.770
	PC3	The use of personal data should always be bound to a specific purpose.	1.96	.732	.704
	PC4	I am more concerned about the disclosure of my personal data on the Internet than most other people.	2.59	.959	.442
	PC5	Companies are collecting too much of my personal data.	1.60	.736	.341
	PC6	Companies should invest more to prevent misuse of my personal data.	1.69	.736	.314
	~~PC7~~	Intelligence agencies like the NSA are collecting too much of my personal data.	1.27	.448	.161
MAX $N = 81$ Mean = 32.37 Reliability: .757 Range: $[6, 54]$ Scale: 9-point semantic	MAX1	No matter how satisfied I am with my job, it is only good for me to watch out for better opportunities.	4.99	1.677	.698
	MAX2	Whenever I am faced with a choice, I try to imagine what all the other possibilities are, even the ones that are not present at the moment.	5.57	1.650	.544
	MAX3	When I watch TV, I channel surf, often scanning through the available options even while attempting to watch one program.	5.40	1.794	.345
	MAX4	I often find it difficult to shop for a gift for a friend.	5.56	1.817	.476
	MAX5	I am a big fan of lists that attempt to rank things (the best movies, the best singers, the best athletes, the best novels, etc.).	5.43	1.774	.451
	MAX6	No matter what I do, I have the highest standards for myself.	5.43	1.774	.496

[a)]Measured for complete scale, i. e, prior to item exclusions. [b)]Measured with Cronbach's α.
[c)]Original questions in German; wording and screenshots are available upon request.
RC = Reverse coded

Table 11: Item pool of the TMC, PCRT, PC, and MAX scales (Study 2). Items with total correlation $\leq .3$ were excluded (crossed out). The summary statistics in the first column apply to the final aggregated scales.

E. SCREENSHOTS

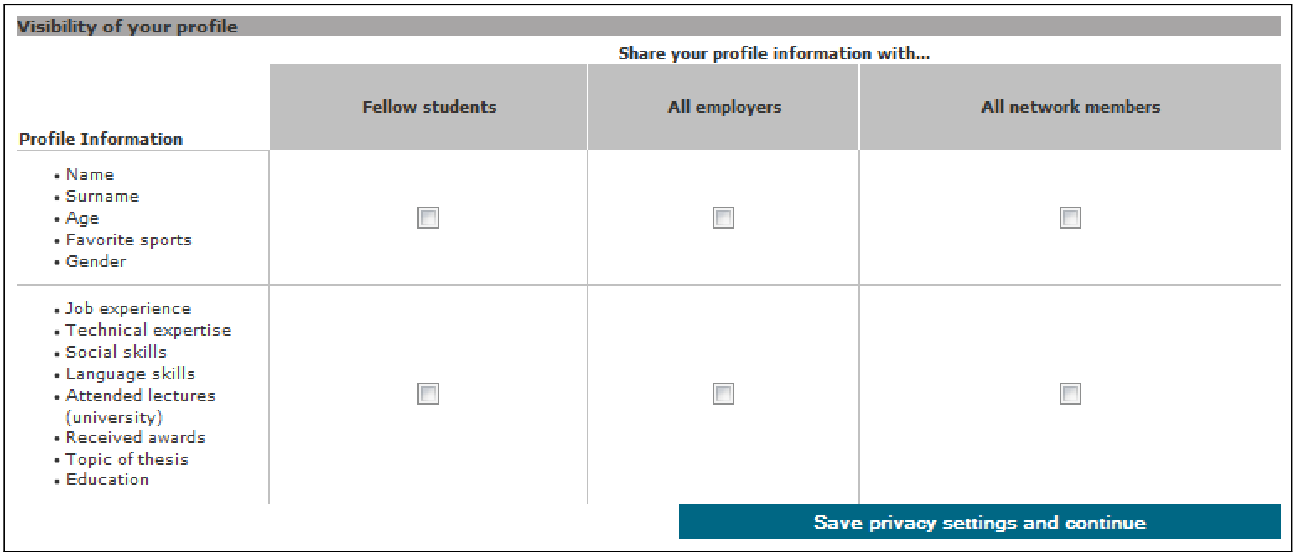

Figure 10: ACM layout for Condition 0: small choice amount and homogenous object structure. (Study 2)

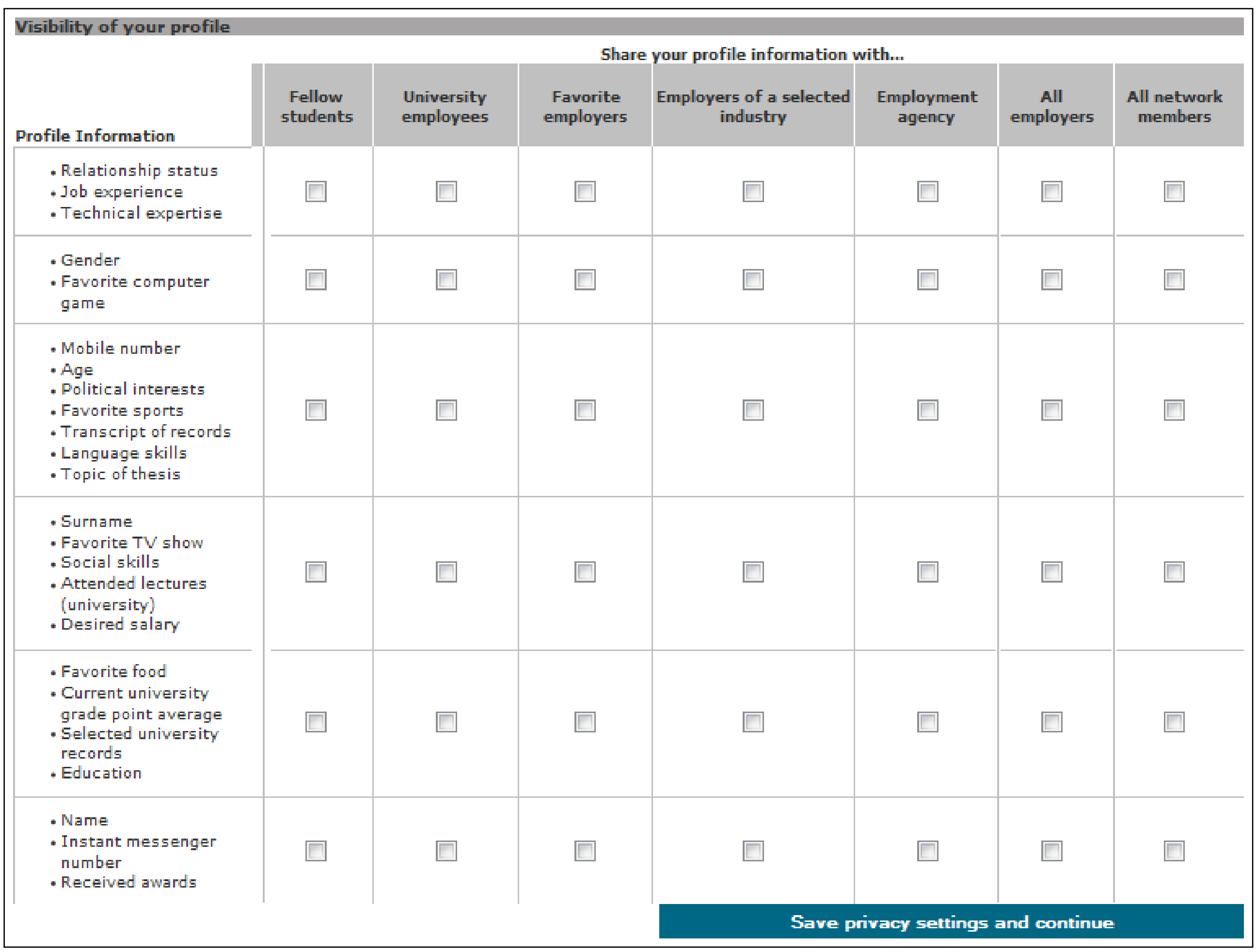

Figure 11: ACM layout for Condition 3: large choice amount and heterogenous object structure. (Study 2)