Title

An Evolutionary Approach to Privacy

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An Evolutionary Approach to Privacy

A thesis submitted in partial satisfaction of the

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by

Sophie Elizabeth Klitgaard

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ABSTRACT OF THE THESIS

An Evolutionary Approach to Privacy

by

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Master of Arts in Anthropology

University of California, Los Angeles, 2024

Professor Daniel Fessler, Co-Chair

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Concerns over privacy are central to many high-profile socio-political debates, yet relatively little empirical research has investigated privacy beyond the realm of digital communications. A dual-inheritance perspective posits i) there are universal psychological mechanisms which evolved via natural selection to regulate the dissemination or withholding of information, and ii) cultural evolutionary processes have given rise to corresponding cultural institutions, including cultural models of privacy. Here, I propose a theoretical model of privacy based on this perspective, in which cultural concepts of privacy are shaped by evolved psychological mechanisms which serve to regulate the transfer of fitness-relevant information towards adaptive ends. I present the results of a U.S. online vignette study that explores some of the core predictions of this model. Results are consistent with the proposed theoretical model, with participants' privacy evaluations predicted by the intentionality of information acquisition, the extent of information transmission, and the identity of the individuals to whom information was transmitted.

The thesis of Sophie Elizabeth Klitgaard is approved.

Richard Alan Clarke Dale

Daniel Fessler, Committee Co-Chair

Harold Clark Barrett, Committee Co-Chair

University of California, Los Angeles

2024

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Acknowledgments

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1.0 Introduction

Concerns over privacy are central to many high-profile debates in digital technology, yet existing research on how privacy manifests in a digital context has produced inconsistent findings (Kokolakis, 2017). For example, numerous authors report observing a "privacy paradox" in online environments: although many individuals claim they value privacy, they willingly disclose personal information for seemingly small rewards (Barth & de Jong, 2017). However, not all authors report observing a gap between the stated value of privacy and behavior in experimental settings (Kokolakis, 2017). Where the phenomena is reported, explanations for its occurrence fall into three contradictory camps: either people are making a) rational risk assessments, b) irrational or biased risk assessments, or c) little to no risk assessments at all (Barth & de Jong, 2017).

One potential cause for such inconsistencies is the reality that, despite the diversity of approaches to studying privacy across the humanities and social sciences, no existing approach addresses, in a single, unifying framework, the psychological mechanisms, cultural norms and institutions, and social processes implicated in privacy attitudes and behavior. Scholars in numerous fields have pointed to the privacy concept's seemingly deep roots in antiquity, and some have discussed the possibility of an evolutionary basis for the cultural concept (Acquisti et al., 2015, 2022). I build on such conjectures, proposing an evolutionary approach to studying privacy which may be illuminative in understanding not only digital privacy, but the diversity of privacy concepts and privacy behavior.

I adopt a dual-inheritance perspective (Richerson & Boyd, 2006), arguing that i) there are universal psychological mechanisms which evolved via natural selection to regulate the dissemination of information, and ii) processes of cultural evolution have given rise to corresponding cultural beliefs, practices, and institutions, including cultural models of privacy. Here, I outline the preliminary components of this framework, and present the results of an empirical study designed to examine some of those components.

1.1 (Evolved) Information Control Mechanisms

Regulating others' access to information poses many adaptive challenges. Extensive evidence indicates that, in numerous species, cognitive abilities to monitor and manipulate information dissemination evolved to further predator avoidance and increase access to mates and other resources. For example, European starlings closely monitor and respond to potential predators' cranial orientation, the presence of eyes, and the direction of eye gaze as cues of predation risk (Carter et al., 2008). Operating within large, complex societies in which social calculus is central to fitness, many non-human primates display comparatively complex social cognition. Chimpanzees, for example, possess an understanding of competing conspecifics' awareness of information about the environment, and utilize this knowledge to gain adaptive advantages (Hare et al., 2000).

The information landscape that humans occupy is markedly more complex due to our dependence on cultural information and linguistic communication. Like all animals, humans acquire information about our environment via direct observation. We produce signals, such as behavioral displays or alarm calls, to convey information to others, and we are sensitive to cues regarding the information others possess. However, unlike other animals, humans are also able to employ symbolic communication, dramatically expanding the quantity of information that can be obtained outside of direct observation.

Additionally, the social landscape in which information dissemination occurs is uniquely complex in humans. For all animals, information transmission beyond the self only holds adaptive significance insofar as it alters the behavior of other organisms in the environment. What matters when a European starling's location is learned by a predator is not simply that the predator's knowledge of the environment has increased, but that the probability that it will attempt to eat the starling is now dramatically higher. Likewise, when a chimpanzee learns that a rival is unaware of a nearby food resource, what matters is not that the chimpanzee now knows something about its competitor that it did not before, but that the probability that the competitor will pursue the resource is significantly lower. Because humans occupy a niche dependent on resource sharing and cooperation with kin and non-kin (Kaplan et al., 2000), how others behave has heightened fitness consequences.

Insofar as information affects the behavior of others, it is worth noting that the consequences of transmission depend in large part on one's position in an information transfer event, and on the content of the information in question. As an obligate social and cultural species, obtaining more information about the physical and social environment generally promotes an individual's fitness. In contrast, however, it is *not* always in an individual's fitness interest to disseminate information. If the information in question may be reputationally harmful or be used by others to gain a competitive advantage, it is generally in one's interests to prevent dissemination. Taking inclusive fitness into account, this same logic suggests that information need not be 'about the self' for there to be an interest in regulating its dissemination. Information that could be reputationally damaging or used to gain a competitive advantage against kin or cooperative partners may also constitute a significant fitness interest.

Of equal importance to the question of who acquires information is the question of the content thereof. Information that is reputationally harmful, for instance, may decrease one's access to shared resources and cooperative partners, and should thus incentivize limiting dissemination (Hess & Hagen, 2023). On the other hand, information that is reputationally beneficial, or which could be used to gain an edge in intragroup competition, may incentivize divulgence (or, at the very least, more lax efforts at restricting dissemination). Notably, what is reputationally valanced or of importance to competition is profoundly shaped by culture—the same action may be interpreted quite differently in different cultures, resulting in different fitness consequences.

Taken together, these ecological realities undoubtedly intensified selection pressures on the ability to regulate the dissemination of information, and plausibly selected for psychological mechanisms in humans which regulate others' acquisition and transmission of information towards broadly adaptive ends. I term this suite of evolved psychological mechanisms **Information Control Mechanisms (ICMs).** ICMs include those cognitive features which enable the monitoring (and control) of:

A) **Other individuals' acquisition of information.** This includes both the ability to assess the likelihood of future acquisition as well as the actuality of current acquisition.
B) **Other individuals' transmission of information**. This includes the ability to assess the probable extent of transmission beyond the initial acquirer, given factors such as the identity of the person acquiring information, the content of the information, and social norms regarding transmission.
C) **The potential consequences of information dissemination.** This includes the ability to assess whether dissemination will be costly or beneficial given one's position in an information transfer event and the content of the information. Building off B), this also includes the ability to assess the identity of the individual to whom the information is transmitted as it relates to the likelihood and ramifications of further transmission.

1.2 Cultural Evolutionary Processes

ICMs alone do not explain the existence of cultural concepts such as privacy. Rather, I argue they are best understood as the product of cultural evolutionary processes, wherein the outputs of ICMs serve as cultural attractors (Buskell, 2017; Sperber, 1996) that bias the transmission and generation of ideas towards relatively stable concepts of privacy. In short, ideas that, within the local cultural constellation of beliefs, values, and norms, have a better 'fit' with ICMs will come to predominate over time.

Groups that are better able to facilitate coordination and cooperation among their members will, all else being equal, be more successful, hence cultural group selection favors the evolution of ideas that facilitate these ends (McElreath et al., 2003). Because of this, cultural evolutionary processes may also favor cultural models of privacy that standardize social norms about what information is and is not appropriate to acquire and spread, facilitating coordination and cooperation in the face of the aforementioned conflict of interests.

Note that the theory outlined above does not predict uniformity in cultural models across groups/societies. Instead, it predicts similarities across cultures in their cultural models of privacy because of the effect of ICMs on cultural evolutionary processes. Because the consequences of dissemination rest on the cultural significance of the information, a given cultural model of privacy will undoubtedly be influenced by the larger body of cultural ideas and norms in the society in which that model exists.

2.0 The Current Study

The present study is an initial attempt to empirically explore some of the core features of this theoretical model. If cultural models of privacy are the product of the interaction between cultural evolutionary processes and the workings of ICMs, then notions of privacy should reflect ICMs such that an individual feels their privacy has been breached when information is acquired and/or transmitted beyond an expected or desired extent. Accordingly, individuals' judgments concerning situations bearing on issues of privacy–judgments that constitute operationalized cultural models of privacy—should center on the monitoring and evaluation of information acquisition and transmission, as well as the potential consequences of information dissemination.

Using vignettes, I sought to measure how select features of an information transfer event, each theoretically central to ICMs, affect U.S. crowdsourced participants' privacy perceptions. Specifically, vignettes varied the (i) manner of acquisition and (ii) extent of information transmission. I measure the effect of varying each of these factors on several outcome variables, including explicit judgments of privacy as well as reports of the participant's moral and emotional responses to the situation.

The content of the information is a key feature of this model and is assumed to play a significant role in cultural models of privacy. The present study controlled for the influence of content by restricting information in the vignettes to one category, personal medical information, as this is commonly considered private in the United States, and neither possession of one's own personal medical information nor attempting to limit its dissemination are likely to be seen as indicating a norm violation or moral failure on the part of the first party.

2.1 Predictions

2.1.1. The manner in which information was acquired, specifically the intentionality on the part of the acquirer, will influence judgments of privacy and related reactions.

If notions of privacy are rooted in the utility of regulating what others know, then a second party's intentional efforts to access one's private information without one's consent should be viewed as the infliction of an unwelcome cost, i.e., a transgression against the self. Likewise, if cultural models of privacy in part include an implicit social contract wherein individuals agree not to pursue certain information about others, then such actions should be viewed as a norm transgression. Previous research has shown that intentionality plays a key, albeit culturally variable, role in moral judgments (Barrett et al., 2016). I therefore predict that, in this U.S. based sample, intentional acquisition and transmission of information from someone without their consent will be judged as more wrong, more harmful, causing greater discomfort, and a greater violation of privacy than non-intentional acts.

2.1.2 Information transmission to a third party should be regarded as a violation of privacy.

The possible cost incurred via information dissemination increases greatly with each additional person to whom information is transmitted. Every additional person is not only a potential competitor or cooperative partner for whom information could play a key role in shaping future behavior, but is also a new node on the transmission chain, multiplying the possibility of future transmission. If cultural models of privacy are closely shaped by ICMs, then the possible risk incurred via information transmission will be reflected in privacy perceptions, such that transmission to a third party will be viewed as more wrong, more harmful, causing greater discomfort, and a greater violation of privacy.

2.1.3. Information transmission to a third party who shares social networks with the first party should be regarded as a greater violation of privacy than transmission to socially unconnected third parties.

A central component of ICMs is the ability to evaluate the consequences of information dissemination insofar as it affects the behavior of others. For most of human history, transmission to individuals who exist in shared social networks likely posed higher risks of fitness-relevant consequences than transmission to socially unconnected individuals. This is true across a range of relationships: upon acquiring a given piece of information, cooperative partners may withhold resources or support, competing individuals may gain an edge, and hostile individuals may be able to cause greater harm. Additionally, linguistic information transmission has, until recently, only been possible via social interaction,[1] and the likelihood of further dissemination is far greater via socially connected individuals than socially unconnected ones (Lind et al., 2007; Miritello et al., 2011). Because ICMs evolved in environments characterized by these key realities, I expect that cues to a second or third party's location in shared social networks will be used as a proxy for the risk associated with information transmission. The increased risk associated with transmission to a socially connected third party should be reflected in privacy-related judgments, such that this transmission will be viewed as more wrong, more harmful, causing greater discomfort, and a greater violation of privacy than transmission to a socially unconnected third party.

3.0 Methods

To test these predictions, I created 12 vignettes, each of which depicted a hypothetical information transfer event between two to three people. The basic vignette structure is as follows:

Person A has personal medical information that Person B learns about.

(In some vignettes) Person B conveys this information to another individual, Person C.

[1] The advent of writing presented some avenues to transmit information without face-to-face social interaction, but even this was historically recent in evolutionary time, and, until very recently, was comparatively limited in quantity.

Each vignette altered a feature of the information transfer event hypothesized to be relevant to privacy perceptions. Participants were assigned one of three base vignettes, each representing one Manner of Acquisition condition. Adding on to each of the three possible base vignettes, participants were shown four Information Transmission conditions.

Following each vignette, participants were asked to evaluate the scenario along four dependent measures: discomfort, wrongness, harmfulness, and violation of privacy. Save for violation of privacy, which was measured on a 4-point scale, all were measured on a balanced 7-point scale. These measures were chosen to allow for multiple indicators of negative reactions to an information transfer event.

Between-subject condition: Manner of Acquisition

Disclosed: Person A knowingly and voluntarily discloses information to Person B

Unintentionally Overheard: Person B unintentionally learns of the information without the knowledge or consent of Person A.

Intentionally Overheard: Person B intentionally learns of the information without the knowledge or consent of Person A.

Within-subjects condition: Information Transmission

Unknown: No additional content is provided indicating information transmission or lack thereof.

None: The vignette states explicitly that Person B did not tell anyone what they had learned.

Socially Unconnected Individual: Person B transmits the information to Person C. Person C is a friend who lives overseas and does not know Person A or anyone else with whom they work.

Socially Connected Individual: Person B transmits the information to Person C. Person C is a mutual colleague of Person A and Person B.

3.1 Participants

A vignette-based survey was deployed via the Prolific crowdsourcing platform. Participants (n=300) were native English speakers, U.S. residents, and between the ages of 18 and 70 (mean age=36), with 134 women and 136 men. Participants were randomly assigned to one of the three base vignettes, each representing one between-subjects variable condition. Participants' responses were removed from the data set for incomplete responses, or survey completion times above 960 or below 120 seconds, leaving n=280 in the final sample (98 in the largest base vignette and 89 in the smallest).

3.2 Data Analysis

For each dependent measure, I used the lme4 and lmertest packages (Bates et al., 2015; Kuznetsova et al., 2017) to fit a two-way linear mixed effects model designed to test the association between Manner of Acquisition and Information Transmission. Information Transmission was a within-subject variable, with each participant shown all four conditions for a given condition of the between-subjects variable. The linear mixed effects model enabled me to account for the lack of independence between repeated observations in Information Transmission as a random effect associated with participant ID, while also taking account for the fixed effects of Manner of Acquisition.

4.0 Results

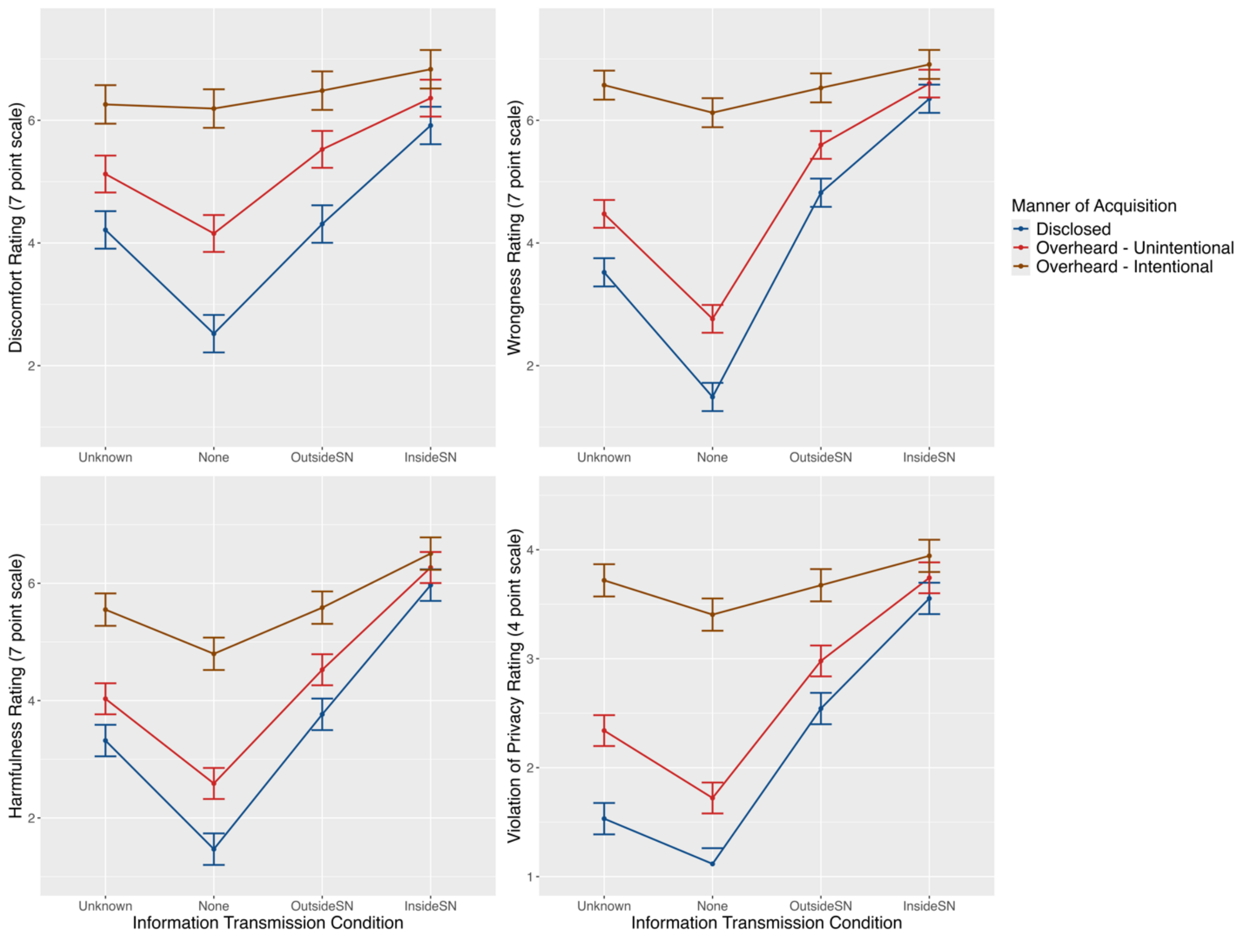

Figure 1. Interactions between Manner of Acquisition and Transmission. Bars indicate 95% CI.

Did the manner in which information was acquired predict privacy-related perceptions?

Yes. Results show that judgments of privacy are affected by intentionality, with participants rating situations in which Person B actively sought to obtain information as significantly more wrong, more harmful, more uncomfortable, and a greater violation of privacy than those in which information was unintentionally obtained. Results show a significant impact of Manner of Acquisition on discomfort (F_2=81.999, $p < .001$), wrongness (F_2=231.299, $p < .001$), harmfulness (F_2=94.326, $p < .001$), and violation of privacy (F_2=191.030, $p < .001$).

Did transmission to a third party predict privacy-related perceptions?

Yes. Results show that judgments of privacy are affected by information transmission beyond the initial recipient of the information. Participants rated vignettes in which Person B transmitted the information to Person C as significantly more uncomfortable, more wrong, more harmful, and a greater violation of privacy than vignettes in which transmission was not mentioned, or situations in which information was explicitly not transmitted. Results show a significant impact of Information Transmission condition on discomfort (F_3=165.124, $p < .001$), wrongness (F_3=567.113, $p < .001$), harmfulness (F_3=484.319, $p < .001$), and violation of privacy (F_3=470.096, $p < .001$).

Did the relative location of the third party within shared social networks predict privacy-related perceptions?

Yes. Results show that, when information transmission to a third party occurs, the location of the third party in social networks shared with the initial information holder predicted increased feelings that the initial holder's privacy had been breached. Tests of contrast between the estimated marginal means showed participants rated transmission to a Socially Unconnected Individual as significantly less uncomfortable (-0.930, $p < .0001$), less wrong (-0.971, $p < .0001$), less harmful (-1.622, $p < .0001$), and less of a violation of privacy (-0.681, $p < .0001$) than transmission to a Socially Connected Individual. For discomfort, wrongness, and harmfulness, these coefficients indicate a near (if not greater than) one point difference in estimated marginal means on the given seven-point scale. Accounting for the variation across Manner of Acquisition conditions generally supported these findings, though notably showed a consistent failure to reach significance in the Intentional Acquisition condition, possibly due to a ceiling effect (see Supplemental Information).

5.0 Discussion

While reflecting the judgments of a limited online sample of Americans, these findings are consonant with the view that notions of privacy reflect the interaction between evolved information-management mechanisms and processes of cultural evolution. More specifically, results indicate that two distinct features of an information transfer event—the way in which information is acquired and the extent of transmission—exert significant influence on perceptions concerning privacy, as well as perceptions of wrongness, harm, and discomfort. Notably, both acquisition and transmission independently predicted evaluations of a privacy violation, with strong interaction effects. In other words, unsanctioned transmission still predicted a violation of privacy even in situations in which the initial disclosure was voluntary.

Evaluations of privacy violations as wrong indicate that privacy behavior may be judged morally. That intentional acquisition on the part of the second party was evaluated as more wrong supports this view.

In terms of transmission, participants appear to consider both the known extent of transmission and the risk of future transmission when making privacy evaluations. Results support the idea that a transmitter's relative location in shared social networks is used as a proxy for the risks associated with transmission, with transmission to socially connected individuals predicting higher privacy violation ratings.

Interestingly, ratings of wrongness, discomfort, harmfulness, and violation of privacy were higher when the existence of future transmission was unknown to participants than when this possibility was explicitly ruled out. This effect could reflect the order in which transmission conditions were presented to participants, with the unknown condition always presented first. Future research is needed to confirm this effect. However, if true, it may indicate that, lacking additional information with which to evaluate risk, participants infer that there is some risk of further transmission.

5.1 Limitations

The present study utilized hypothetical situations in which participants were asked to adopt the perspective of someone else. Because of this, participants' responses may differ from how they would actually react in a given situation.

Additionally, an important limitation of the present study is that the sample and vignettes used are specific to an English-speaking, North American cultural context. Future work is needed to document both similarities and differences in cultural models of privacy and their deployment across disparate cultures and contexts.

5.2 Future Directions

The goal of the present study was to outline an evolutionary approach to understanding privacy and examine some of the foundational predictions of that approach. As such, there are a multitude of features of this model that remain to be explored.

First, the present study did not evaluate how varying one's position in an information transfer event might affect privacy perceptions. Actors in such an event will often have opposing fitness interests in information dissemination. While it is in the first party's fitness interest to regulate dissemination, all other individuals may benefit by acquiring the information in question. If cultural models of privacy are shaped by ICMs which evolved to regulate information dissemination towards adaptive ends, then the different costs of dissemination engendered by an individual's position in an information transfer event should be reflected in privacy perceptions. Additional studies are needed to empirically demonstrate this relationship.

Second, the present study did not examine how variation in the content of the information might affect privacy perceptions. Further studies are necessary to examine this relationship. In particular, the moral valence and reputational impact of a given piece of information will likely have a substantial effect on privacy-relevant reasoning, as these factors alter the risks associated with information dissemination. These risks should differ significantly based on one's position in a given information transfer event, as individuals attempt to seek out information regarding cooperative and competitive partners while at the same time trying to limit the dissemination of reputationally damaging or otherwise costly information.

Additionally, further studies are needed to evaluate the degree to which individuals' performance of 'privacy calculus,' (Dinev & Hart, 2006) is affected by the presence of evolutionarily salient cues in a given information transfer event. In this sense, what Acquisti et al. (2022) refer to as the 'privacy gap' can be understood as an evolutionary mismatch between evolved information-management psychology and the contemporary information landscape engendered by digital communication technology.

Lastly, a dual-inheritance perspective predicts both that core components of cultural models of privacy will be shared across disparate cultures, and that many specific features thereof–critically including what information is considered private, and who is entitled to acquire and transmit private information–will vary substantially across cultures. Influences on variation in cultural models of privacy across groups remain to be studied. Variation across cultures may be driven by factors such as the scale of communities and social networks, the degree of social and economic interdependence, tolerance for norm non-adherence, and so on. Additionally, it remains to be seen how variation in systems of information dissemination within cultures may influence individual and group conceptualizations of privacy-related behavior. For example, one's relative position in hierarchical power structures may change their access to information and attitudes regarding dissemination. In short, the present study reflects a first step in the exploration of a phenomenon that is both central to many current issues and woefully understudied.

An Evolutionary Approach to Privacy

Supplemental Information

The following supplement contains the results of the two-way linear mixed effects models and corresponding tests of estimated marginal means for each of four dependent variables.

Table of Contents:

1. Variables

Variable Name	Variable Name (shortened)	Independent vs Dependent	Variable Description	Levels	Level Description
Manner of Acquisition	InfoAcq_f	Independent	How the information was acquired by Person B	3	1: Disclosed, 2: Overheard - Unintentional, 3: Overheard - Intentional)
Information Transmission	InfoTrans_f	Independent	If information was transmitted beyond Person B (to Person C) and, if information was transmitted, the identity of Person C relative to Person A.	4	1: Unknown - no information given in the vignette on transmission, 2: None - no information transmission occurred, 3: Outside Social Network - information was transmitted to Person C, who is not socially connected to Person A, 4: Inside Social Network - information was

					transmitted to Person C, who is socially connected to Person A
Discomfort	Discomfort	Dependent	Participants evaluate how they would feel in a given vignette on a scale from 1 - 7, with 1 being "very comfortable" and 7 being "very uncomfortable."	7	1: Very comfortable, 2: Somewhat comfortable, 3: A little comfortable, 4: Neither comfortable nor uncomfortable, 5: A little uncomfortable, 6: Somewhat uncomfortable, 7: Very uncomfortable
Wrong	Wrong	Dependent	Participants evaluate Person B's actions in a given vignette on a scale from 1 - 7, with 1 being "very right" and 7 being "very wrong."	7	1: Very right, 2: Somewhat right, 3: A little right, 4: Neither right nor wrong, 5: A little wrong, 6: Somewhat wrong, 7: Very wrong
Harmfulness	Harmfulness	Dependent	Participants evaluate Person B's actions in a given vignette on a scale from 1 - 7, with 1 being "very harmless" and 7 being "very harmful."	7	1: Very harmless, 2: Somewhat harmless, 3: A little harmless, 4: Neither harmless nor harmful, 5: A little harmful, 6: Somewhat harmful, 7: Very harmful
Violation of Privacy	Violate	Dependent	Participants evaluate the degree to which the scenario violated Person A's privacy on a scale from 1 - 4, 1 being "did not violate my privacy at all" and 4 being "violated my privacy a lot."	4	1: Did not violate my privacy at all, 2: Violated my privacy a little, 3: Violated my privacy somewhat, 4: Violated my privacy a lot

2. Linear Mixed Effects Model: Discomfort

```
> m1<-lmerTest::lmer(Discomfort~InfoTrans_f*InfoAcq_f+(1|Response_ID),data=d)
> sum_m1<-summary(m1)
> print(sum_m1)

Linear mixed model fit by REML. t-tests use Satterthwaite's method
['lmerModLmerTest']
Formula: Discomfort ~ InfoTrans_f * InfoAcq_f + (1 | Response_ID)
   Data: d

REML criterion at convergence: 3843.4

Scaled residuals: 
    Min      1Q  Median      3Q     Max 
-4.0744 -0.4181  0.0906  0.4571  2.9001 

Random effects:
 Groups      Name        Variance Std.Dev.
 Response_ID (Intercept) 1.042    1.021   
 Residual                1.238    1.113   
Number of obs: 1120, groups:  Response_ID, 280

Fixed effects:
```

```
                                              Estimate Std. Error        df t
value Pr(>|t|)
(Intercept)                                    4.21277    0.15573 681.12396
27.052  < 2e-16 ***
InfoTrans_fNone                               -1.69149    0.16228 831.00000 -
10.423  < 2e-16 ***
InfoTrans_fOutsideSN                           0.09574    0.16228 831.00000
0.590  0.55535
InfoTrans_fInsideSN                            1.70213    0.16228 831.00000
10.489  < 2e-16 ***
InfoAcq_fOverheardUnIn                         0.91095    0.21852 681.12395
4.169 3.46e-05 ***
InfoAcq_fOverheardIn                           2.04566    0.22331 681.12395
9.161  < 2e-16 ***
InfoTrans_fNone:InfoAcq_fOverheardUnIn         0.72242    0.22771 831.00000
3.172  0.00157 **
InfoTrans_fOutsideSN:InfoAcq_fOverheardUnIn    0.30632    0.22771 831.00000
1.345  0.17893
InfoTrans_fInsideSN:InfoAcq_fOverheardUnIn    -0.46501    0.22771 831.00000  -
2.042  0.04146 *
InfoTrans_fNone:InfoAcq_fOverheardIn           1.62407    0.23270 831.00000
6.979 6.06e-12 ***
InfoTrans_fOutsideSN:InfoAcq_fOverheardIn      0.12897    0.23270 831.00000
0.554  0.57955
InfoTrans_fInsideSN:InfoAcq_fOverheardIn      -1.12909    0.23270 831.00000  -
4.852 1.46e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
             (Intr) InfT_N InT_OSN InT_ISN IA_OUI InA_OI IT_N:IA_OU
IT_OSN:IA_OU IT_ISN:IA_OU IT_N:IA_OI
InfTrns_fNn  -0.521
InfTrns_OSN  -0.521  0.500
InfTrns_ISN  -0.521  0.500  0.500
InfAcq_fOUI  -0.713  0.371  0.371   0.371
InfAcq_fOvI  -0.697  0.363  0.363   0.363   0.497
IT_N:IA_OUI   0.371 -0.713 -0.356  -0.356  -0.521 -0.259
IT_OSN:IA_OU  0.371 -0.356 -0.713  -0.356  -0.521 -0.259  0.500
IT_ISN:IA_OU  0.371 -0.356 -0.356  -0.713  -0.521 -0.259  0.500      0.500
InT_N:IA_OI   0.363 -0.697 -0.349  -0.349  -0.259 -0.521  0.497      0.248
0.248
IT_OSN:IA_OI  0.363 -0.349 -0.697  -0.349  -0.259 -0.521  0.248      0.497
0.248        0.500
IT_ISN:IA_OI  0.363 -0.349 -0.349  -0.697  -0.259 -0.521  0.248      0.248
0.497        0.500
             IT_OSN:IA_OI
InfTrns_fNn
InfTrns_OSN
InfTrns_ISN
InfAcq_fOUI
InfAcq_fOvI
IT_N:IA_OUI
IT_OSN:IA_OU
IT_ISN:IA_OU
InT_N:IA_OI
IT_OSN:IA_OI
```

```
IT_ISN:IA_OI  0.500

> confint(m1)
Computing profile confidence intervals ...
                                                    2.5 %      97.5 %
.sig01                                          0.9106663  1.13162672
.sigma                                          1.0556650  1.16163869
(Intercept)                                     3.9087580  4.51677388
InfoTrans_fNone                                -2.0082006 -1.37477817
InfoTrans_fOutsideSN                           -0.2209665  0.41245587
InfoTrans_fInsideSN                             1.3854165  2.01883885
InfoAcq_fOverheardUnIn                          0.4843504  1.33754034
InfoAcq_fOverheardIn                            1.6097323  2.48158969
InfoTrans_fNone:InfoAcq_fOverheardUnIn          0.2779966  1.16683784
InfoTrans_fOutsideSN:InfoAcq_fOverheardUnIn    -0.1381035  0.75073782
InfoTrans_fInsideSN:InfoAcq_fOverheardUnIn     -0.9094349 -0.02059361
InfoTrans_fNone:InfoAcq_fOverheardIn            1.1699292  2.07821802
InfoTrans_fOutsideSN:InfoAcq_fOverheardIn      -0.3251700  0.58311881
InfoTrans_fInsideSN:InfoAcq_fOverheardIn       -1.5832383 -0.67494957

> anova(m1)
Type III Analysis of Variance Table with Satterthwaite's method
                      Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
InfoTrans_f           613.12 204.373     3   831 165.124 < 2.2e-16 ***
InfoAcq_f             202.98 101.489     2   277  81.999 < 2.2e-16 ***
InfoTrans_f:InfoAcq_f 178.60  29.766     6   831  24.050 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> BIC(m1)
[1] 3941.712
```

2a. Estimated Marginal Means of Discomfort, Averaging over Manner of Acquisition

```
> emm_m1.1 <- emmeans(m1, specs=c("InfoTrans_f"))
NOTE: Results may be misleading due to involvement in interactions
> emm_m1.1
 InfoTrans_f emmean     SE  df lower.CL upper.CL
 Unknown       5.20 0.0903 681     5.02     5.38
 None          4.29 0.0903 681     4.11     4.47
 OutsideSN     5.44 0.0903 681     5.26     5.62
 InsideSN      6.37 0.0903 681     6.19     6.55

Results are averaged over the levels of: InfoAcq_f
Degrees-of-freedom method: kenward-roger
Confidence level used: 0.95

> contrast(emm_m1.1, method="pairwise",simple="InfoTrans_f")
contrast              estimate     SE  df t.ratio p.value
Unknown - None           0.909 0.0941 831   9.665  <.0001
Unknown - OutsideSN     -0.241 0.0941 831  -2.560  0.0519
Unknown - InsideSN      -1.171 0.0941 831 -12.444  <.0001
None - OutsideSN        -1.150 0.0941 831 -12.225  <.0001
None - InsideSN         -2.080 0.0941 831 -22.109  <.0001
OutsideSN - InsideSN    -0.930 0.0941 831  -9.884  <.0001
```

```
Results are averaged over the levels of: InfoAcq_f
Degrees-of-freedom method: kenward-roger
P value adjustment: tukey method for comparing a family of 4 estimates
```

2b. Estimated Marginal Means of Discomfort, Specifying Manner of Acquisition

```
>emm_m1 <- emmeans(m1, specs=c("InfoTrans_f", "InfoAcq_f"))
> emm_m1
 InfoTrans_f InfoAcq_f     emmean    SE  df lower.CL upper.CL
 Unknown     Disclosed       4.21 0.156 681     3.91     4.52
 None        Disclosed       2.52 0.156 681     2.22     2.83
 OutsideSN   Disclosed       4.31 0.156 681     4.00     4.61
 InsideSN    Disclosed       5.91 0.156 681     5.61     6.22
 Unknown     OverheardUnIn   5.12 0.153 681     4.82     5.42
 None        OverheardUnIn   4.15 0.153 681     3.85     4.46
 OutsideSN   OverheardUnIn   5.53 0.153 681     5.22     5.83
 InsideSN    OverheardUnIn   6.36 0.153 681     6.06     6.66
 Unknown     OverheardIn     6.26 0.160 681     5.94     6.57
 None        OverheardIn     6.19 0.160 681     5.88     6.51
 OutsideSN   OverheardIn     6.48 0.160 681     6.17     6.80
 InsideSN    OverheardIn     6.83 0.160 681     6.52     7.15

Degrees-of-freedom method: kenward-roger
Confidence level used: 0.95

> contrast(emm_m1, method="pairwise",simple="InfoTrans_f")
InfoAcq_f = Disclosed:
 contrast             estimate    SE  df t.ratio p.value
 Unknown - None         1.6915 0.162 831  10.423  <.0001
 Unknown - OutsideSN   -0.0957 0.162 831  -0.590  0.9351
 Unknown - InsideSN    -1.7021 0.162 831 -10.489  <.0001
 None - OutsideSN      -1.7872 0.162 831 -11.013  <.0001
 None - InsideSN       -3.3936 0.162 831 -20.912  <.0001
 OutsideSN - InsideSN  -1.6064 0.162 831  -9.899  <.0001

InfoAcq_f = OverheardUnIn:
 contrast             estimate    SE  df t.ratio p.value
 Unknown - None         0.9691 0.160 831   6.066  <.0001
 Unknown - OutsideSN   -0.4021 0.160 831  -2.517  0.0581
 Unknown - InsideSN    -1.2371 0.160 831  -7.744  <.0001
 None - OutsideSN      -1.3711 0.160 831  -8.583  <.0001
 None - InsideSN       -2.2062 0.160 831 -13.810  <.0001
 OutsideSN - InsideSN  -0.8351 0.160 831  -5.227  <.0001

InfoAcq_f = OverheardIn:
 contrast             estimate    SE  df t.ratio p.value
 Unknown - None         0.0674 0.167 831   0.404  0.9777
 Unknown - OutsideSN   -0.2247 0.167 831  -1.347  0.5329
 Unknown - InsideSN    -0.5730 0.167 831  -3.436  0.0035
 None - OutsideSN      -0.2921 0.167 831  -1.752  0.2977
 None - InsideSN       -0.6404 0.167 831  -3.840  0.0008
 OutsideSN - InsideSN  -0.3483 0.167 831  -2.089  0.1576
```

3. Linear Mixed Effects Model: Wrongness

```
>m2<-lmerTest::lmer(Wrong~InfoTrans_f*InfoAcq_f+(1|Response_ID),data=d)
```

```
> sum_m2<-summary(m2)
> print(sum_m2)
Linear mixed model fit by REML. t-tests use Satterthwaite's method
['lmerModLmerTest']
Formula: Wrong ~ InfoTrans_f * InfoAcq_f + (1 | Response_ID)
   Data: d

REML criterion at convergence: 3350.4

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.5174 -0.4249  0.0656  0.5262  3.2739

Random effects:
 Groups      Name        Variance Std.Dev.
 Response_ID (Intercept) 0.4135   0.6431
 Residual                0.8803   0.9382
Number of obs: 1120, groups:  Response_ID, 280

Fixed effects:
                                            Estimate Std. Error       df t
value Pr(>|t|)
(Intercept)                                   3.5213     0.1173 848.0782
30.014  < 2e-16 ***
InfoTrans_fNone                              -2.0319     0.1369 831.0000 -
14.847  < 2e-16 ***
InfoTrans_fOutsideSN                          1.2979     0.1369 831.0000
9.484  < 2e-16 ***
InfoTrans_fInsideSN                           2.8298     0.1369 831.0000
20.677  < 2e-16 ***
InfoAcq_fOverheardUnIn                        0.9530     0.1646 848.0782
5.789 9.99e-09 ***
InfoAcq_fOverheardIn                          3.0518     0.1682 848.0782
18.140  < 2e-16 ***
InfoTrans_fNone:InfoAcq_fOverheardUnIn        0.3206     0.1920 831.0000
1.669 0.095431 .
InfoTrans_fOutsideSN:InfoAcq_fOverheardUnIn  -0.1742     0.1920 831.0000  -
0.907 0.364721
InfoTrans_fInsideSN:InfoAcq_fOverheardUnIn   -0.7061     0.1920 831.0000  -
3.677 0.000251 ***
InfoTrans_fNone:InfoAcq_fOverheardIn          1.5825     0.1962 831.0000
8.064 2.57e-15 ***
InfoTrans_fOutsideSN:InfoAcq_fOverheardIn    -1.3428     0.1962 831.0000  -
6.843 1.51e-11 ***
InfoTrans_fInsideSN:InfoAcq_fOverheardIn     -2.4927     0.1962 831.0000 -
12.702  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
             (Intr) InfT_N InT_OSN InT_ISN IA_OUI InA_OI IT_N:IA_OU
IT_OSN:IA_OU IT_ISN:IA_OU IT_N:IA_OI
InfTrns_fNn  -0.583
InfTrns_OSN  -0.583  0.500
InfTrns_ISN  -0.583  0.500  0.500
InfAcq_fOUI  -0.713  0.416  0.416   0.416
```

```
InfAcq_fOvI  -0.697  0.407  0.407   0.407   0.497
IT_N:IA_OUI   0.416 -0.713 -0.356  -0.356  -0.583 -0.290
IT_OSN:IA_OU  0.416 -0.356 -0.713  -0.356  -0.583 -0.290  0.500
IT_ISN:IA_OU  0.416 -0.356 -0.356  -0.713  -0.583 -0.290  0.500      0.500
InT_N:IA_OI   0.407 -0.697 -0.349  -0.349  -0.290 -0.583  0.497      0.248
0.248
IT_OSN:IA_OI  0.407 -0.349 -0.697  -0.349  -0.290 -0.583  0.248      0.497
0.248        0.500
IT_ISN:IA_OI  0.407 -0.349 -0.349  -0.697  -0.290 -0.583  0.248      0.248
0.497        0.500
             IT_OSN:IA_OI
InfTrns_fNn
InfTrns_OSN
InfTrns_ISN
InfAcq_fOUI
InfAcq_fOvI
IT_N:IA_OUI
IT_OSN:IA_OU
IT_ISN:IA_OU
InT_N:IA_OI
IT_OSN:IA_OI
IT_ISN:IA_OI  0.500
```

```
> confint(m2)
Computing profile confidence intervals ...
                                                  2.5 %     97.5 %
.sig01                                       0.55960936  0.7260432
.sigma                                       0.89028160  0.9796531
(Intercept)                                  3.29231287  3.7502403
InfoTrans_fNone                             -2.29900923 -1.7648206
InfoTrans_fOutsideSN                         1.03077801  1.5649667
InfoTrans_fInsideSN                          2.56269290  3.0968816
InfoAcq_fOverheardUnIn                       0.63165999  1.2742404
InfoAcq_fOverheardIn                         2.72343720  3.3800770
InfoTrans_fNone:InfoAcq_fOverheardUnIn      -0.05422178  0.6953712
InfoTrans_fOutsideSN:InfoAcq_fOverheardUnIn -0.54895747  0.2006355
InfoTrans_fInsideSN:InfoAcq_fOverheardUnIn  -1.08087236 -0.3312794
InfoTrans_fNone:InfoAcq_fOverheardIn         1.19947983  1.9654736
InfoTrans_fOutsideSN:InfoAcq_fOverheardIn   -1.72581302 -0.9598193
InfoTrans_fInsideSN:InfoAcq_fOverheardIn    -2.87570545 -2.1097117
```

```
> anova(m2)
Type III Analysis of Variance Table with Satterthwaite's method
                       Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
InfoTrans_f           1497.64  499.21     3   831 567.113 < 2.2e-16 ***
InfoAcq_f              407.21  203.61     2   277 231.299 < 2.2e-16 ***
InfoTrans_f:InfoAcq_f  461.97   77.00     6   831  87.468 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> BIC(m2)
[1] 3448.714
```

3a. Estimated Marginal Means of Wrongness, Averaging over Manner of Acquisition

```
> emm_m2.1 <- emmeans(m2, specs=c("InfoTrans_f"))
```

```
NOTE: Results may be misleading due to involvement in interactions
> emm_m2.1
 InfoTrans_f emmean    SE  df lower.CL upper.CL
 Unknown       4.86 0.068 848     4.72     4.99
 None          3.46 0.068 848     3.33     3.59
 OutsideSN     5.65 0.068 848     5.51     5.78
 InsideSN      6.62 0.068 848     6.49     6.75

Results are averaged over the levels of: InfoAcq_f
Degrees-of-freedom method: kenward-roger
Confidence level used: 0.95
> contrast(emm_m2.1, method="pairwise",simple="InfoTrans_f")
 contrast              estimate     SE  df t.ratio p.value
 Unknown - None           1.398 0.0793 831  17.614  <.0001
 Unknown - OutsideSN     -0.792 0.0793 831  -9.984  <.0001
 Unknown - InsideSN      -1.764 0.0793 831 -22.226  <.0001
 None - OutsideSN        -2.190 0.0793 831 -27.598  <.0001
 None - InsideSN         -3.161 0.0793 831 -39.840  <.0001
 OutsideSN - InsideSN    -0.971 0.0793 831 -12.242  <.0001

Results are averaged over the levels of: InfoAcq_f
Degrees-of-freedom method: kenward-roger
P value adjustment: tukey method for comparing a family of 4 estimates
```

3b. Estimated Marginal Means of Wrongness, Specifying Manner of Acquisition

```
> emm_m2 <- emmeans(m2, specs=c("InfoTrans_f", "InfoAcq_f"))
> emm_m2
 InfoTrans_f InfoAcq_f      emmean    SE  df lower.CL upper.CL
 Unknown     Disclosed        3.52 0.117 848     3.29     3.75
 None        Disclosed        1.49 0.117 848     1.26     1.72
 OutsideSN   Disclosed        4.82 0.117 848     4.59     5.05
 InsideSN    Disclosed        6.35 0.117 848     6.12     6.58
 Unknown     OverheardUnIn    4.47 0.115 848     4.25     4.70
 None        OverheardUnIn    2.76 0.115 848     2.54     2.99
 OutsideSN   OverheardUnIn    5.60 0.115 848     5.37     5.82
 InsideSN    OverheardUnIn    6.60 0.115 848     6.37     6.82
 Unknown     OverheardIn      6.57 0.121 848     6.34     6.81
 None        OverheardIn      6.12 0.121 848     5.89     6.36
 OutsideSN   OverheardIn      6.53 0.121 848     6.29     6.76
 InsideSN    OverheardIn      6.91 0.121 848     6.67     7.15

Degrees-of-freedom method: kenward-roger
Confidence level used: 0.95

> contrast(emm_m2, method="pairwise",simple="InfoTrans_f")
InfoAcq_f = Disclosed:
 contrast              estimate    SE  df t.ratio p.value
 Unknown - None          2.0319 0.137 831  14.847  <.0001
 Unknown - OutsideSN    -1.2979 0.137 831  -9.484  <.0001
 Unknown - InsideSN     -2.8298 0.137 831 -20.677  <.0001
 None - OutsideSN       -3.3298 0.137 831 -24.331  <.0001
 None - InsideSN        -4.8617 0.137 831 -35.525  <.0001
 OutsideSN - InsideSN   -1.5319 0.137 831 -11.194  <.0001

InfoAcq_f = OverheardUnIn:
```

```
 contrast              estimate    SE  df t.ratio p.value
 Unknown - None          1.7113 0.135 831  12.703  <.0001
 Unknown - OutsideSN    -1.1237 0.135 831  -8.341  <.0001
 Unknown - InsideSN     -2.1237 0.135 831 -15.764  <.0001
 None - OutsideSN       -2.8351 0.135 831 -21.044  <.0001
 None - InsideSN        -3.8351 0.135 831 -28.467  <.0001
 OutsideSN - InsideSN   -1.0000 0.135 831  -7.423  <.0001

InfoAcq_f = OverheardIn:
 contrast              estimate    SE  df t.ratio p.value
 Unknown - None          0.4494 0.141 831   3.196  0.0079
 Unknown - OutsideSN     0.0449 0.141 831   0.320  0.9887
 Unknown - InsideSN     -0.3371 0.141 831  -2.397  0.0785
 None - OutsideSN       -0.4045 0.141 831  -2.876  0.0215
 None - InsideSN        -0.7865 0.141 831  -5.592  <.0001
 OutsideSN - InsideSN   -0.3820 0.141 831  -2.716  0.0340

Degrees-of-freedom method: kenward-roger
P value adjustment: tukey method for comparing a family of 4 estimates
```

4. Linear Mixed Effects Model: Harmfulness

```
>m3<-lmerTest::lmer(Harmfulness~InfoTrans_f*InfoAcq_f+(1|Response_ID),data=d)
> sum_m3<-summary(m3)
> print(sum_m3)
Linear mixed model fit by REML. t-tests use Satterthwaite's method
['lmerModLmerTest']
Formula: Harmfulness ~ InfoTrans_f * InfoAcq_f + (1 | Response_ID)
   Data: d

REML criterion at convergence: 3621.8

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.6127 -0.5223  0.0475  0.5626  2.8298

Random effects:
 Groups      Name        Variance Std.Dev.
 Response_ID (Intercept) 0.7038   0.8389
 Residual                1.0593   1.0292
Number of obs: 1120, groups:  Response_ID, 280

Fixed effects:
                                             Estimate Std. Error        df t
value Pr(>|t|)
(Intercept)                                   3.31915    0.13695 749.63125
24.236  < 2e-16 ***
InfoTrans_fNone                              -1.85106    0.15012 831.00000 -
12.330  < 2e-16 ***
InfoTrans_fOutsideSN                          0.44681    0.15012 831.00000
2.976 0.003003 **
InfoTrans_fInsideSN                           2.64894    0.15012 831.00000
17.645  < 2e-16 ***
InfoAcq_fOverheardUnIn                        0.71178    0.19218 749.63125
3.704 0.000228 ***
```

```
InfoAcq_fOverheardIn                          2.23141    0.19638 749.63125
11.363  < 2e-16 ***
InfoTrans_fNone:InfoAcq_fOverheardUnIn        0.40776    0.21066 831.00000
1.936 0.053249 .
InfoTrans_fOutsideSN:InfoAcq_fOverheardUnIn   0.04804    0.21066 831.00000
0.228 0.819679
InfoTrans_fInsideSN:InfoAcq_fOverheardUnIn   -0.41182    0.21066 831.00000  -
1.955 0.050928 .
InfoTrans_fNone:InfoAcq_fOverheardIn          1.09825    0.21527 831.00000
5.102 4.17e-07 ***
InfoTrans_fOutsideSN:InfoAcq_fOverheardIn    -0.41310    0.21527 831.00000  -
1.919 0.055327 .
InfoTrans_fInsideSN:InfoAcq_fOverheardIn     -1.69388    0.21527 831.00000  -
7.869 1.11e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
             (Intr) InfT_N InT_OSN InT_ISN IA_OUI InA_OI IT_N:IA_OU
IT_OSN:IA_OU IT_ISN:IA_OU IT_N:IA_OI
InfTrns_fNn  -0.548
InfTrns_OSN  -0.548  0.500
InfTrns_ISN  -0.548  0.500  0.500
InfAcq_fOUI  -0.713  0.391  0.391   0.391
InfAcq_fOvI  -0.697  0.382  0.382   0.382   0.497
IT_N:IA_OUI   0.391 -0.713 -0.356  -0.356  -0.548 -0.272
IT_OSN:IA_OU  0.391 -0.356 -0.713  -0.356  -0.548 -0.272  0.500
IT_ISN:IA_OU  0.391 -0.356 -0.356  -0.713  -0.548 -0.272  0.500      0.500
InT_N:IA_OI   0.382 -0.697 -0.349  -0.349  -0.272 -0.548  0.497      0.248
0.248
IT_OSN:IA_OI  0.382 -0.349 -0.697  -0.349  -0.272 -0.548  0.248      0.497
0.248        0.500
IT_ISN:IA_OI  0.382 -0.349 -0.349  -0.697  -0.272 -0.548  0.248      0.248
0.497        0.500
             IT_OSN:IA_OI
InfTrns_fNn
InfTrns_OSN
InfTrns_ISN
InfAcq_fOUI
InfAcq_fOvI
IT_N:IA_OUI
IT_OSN:IA_OU
IT_ISN:IA_OU
InT_N:IA_OI
IT_OSN:IA_OI
IT_ISN:IA_OI  0.500

> confint(m3)
Computing profile confidence intervals ...
                                                2.5 %       97.5 %
.sig01                                    0.742367642  0.9358219960
.sigma                                    0.976607933  1.0746454058
(Intercept)                               3.051830268  3.5864676043
InfoTrans_fNone                          -2.144057021 -1.5580706386
InfoTrans_fOutsideSN                      0.153815319  0.7398017018
InfoTrans_fInsideSN                       2.355942979  2.9419293614
InfoAcq_fOverheardUnIn                    0.336667635  1.0868901626
```

```
InfoAcq_fOverheardIn                          1.848094317  2.6147314059
InfoTrans_fNone:InfoAcq_fOverheardUnIn       -0.003373826  0.8189035475
InfoTrans_fOutsideSN:InfoAcq_fOverheardUnIn -0.363101837  0.4591755370
InfoTrans_fInsideSN:InfoAcq_fOverheardUnIn  -0.822961455 -0.0006840813
InfoTrans_fNone:InfoAcq_fOverheardIn          0.678120608  1.5183890737
InfoTrans_fOutsideSN:InfoAcq_fOverheardIn   -0.833234878  0.0070335872
InfoTrans_fInsideSN:InfoAcq_fOverheardIn    -2.114014223 -1.2737457577

> anova(m3)
Type III Analysis of Variance Table with Satterthwaite's method
                     Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)    
InfoTrans_f         1539.05  513.02     3   831 484.319 < 2.2e-16 ***
InfoAcq_f            199.83   99.92     2   277  94.326 < 2.2e-16 ***
InfoTrans_f:InfoAcq_f 193.65  32.28     6   831  30.470 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> BIC(m3)
[1] 3720.097
```

4a. Estimated Marginal Means of Harmfulness, Averaging over Manner of Acquisition

```
> emm_m3.1 <- emmeans(m3, specs=c("InfoTrans_f"))
NOTE: Results may be misleading due to involvement in interactions
> emm_m3.1
 InfoTrans_f emmean     SE  df lower.CL upper.CL
 Unknown       4.30 0.0794 750     4.14     4.46
 None          2.95 0.0794 750     2.80     3.11
 OutsideSN     4.63 0.0794 750     4.47     4.78
 InsideSN      6.25 0.0794 750     6.09     6.40

Results are averaged over the levels of: InfoAcq_f 
Degrees-of-freedom method: kenward-roger 
Confidence level used: 0.95 

> contrast(emm_m3.1, method="pairwise",simple="InfoTrans_f")
 contrast              estimate    SE  df t.ratio p.value
 Unknown - None           1.349 0.087 831  15.500  <.0001
 Unknown - OutsideSN     -0.325 0.087 831  -3.735  0.0011
 Unknown - InsideSN      -1.947 0.087 831 -22.370  <.0001
 None - OutsideSN        -1.674 0.087 831 -19.235  <.0001
 None - InsideSN         -3.296 0.087 831 -37.869  <.0001
 OutsideSN - InsideSN    -1.622 0.087 831 -18.634  <.0001

Results are averaged over the levels of: InfoAcq_f 
Degrees-of-freedom method: kenward-roger 
P value adjustment: tukey method for comparing a family of 4 estimates 
```

4b. Estimated Marginal Means of Harmfulness, Specifying Manner of Acquisition

```
> emm_m3 <- emmeans(m3, specs=c("InfoTrans_f", "InfoAcq_f"))
> emm_m3
 InfoTrans_f InfoAcq_f     emmean    SE  df lower.CL upper.CL
 Unknown     Disclosed       3.32 0.137 750     3.05     3.59
 None        Disclosed       1.47 0.137 750     1.20     1.74
 OutsideSN   Disclosed       3.77 0.137 750     3.50     4.03
```

```
 InsideSN    Disclosed       5.97 0.137 750     5.70     6.24
 Unknown     OverheardUnIn   4.03 0.135 750     3.77     4.30
 None        OverheardUnIn   2.59 0.135 750     2.32     2.85
 OutsideSN   OverheardUnIn   4.53 0.135 750     4.26     4.79
 InsideSN    OverheardUnIn   6.27 0.135 750     6.00     6.53
 Unknown     OverheardIn     5.55 0.141 750     5.27     5.83
 None        OverheardIn     4.80 0.141 750     4.52     5.07
 OutsideSN   OverheardIn     5.58 0.141 750     5.31     5.86
 InsideSN    OverheardIn     6.51 0.141 750     6.23     6.78

Degrees-of-freedom method: kenward-roger
Confidence level used: 0.95

> contrast(emm_m3, method="pairwise",simple="InfoTrans_f")
InfoAcq_f = Disclosed:
 contrast              estimate    SE  df t.ratio p.value
 Unknown - None          1.8511 0.150 831  12.330  <.0001
 Unknown - OutsideSN    -0.4468 0.150 831  -2.976  0.0159
 Unknown - InsideSN     -2.6489 0.150 831 -17.645  <.0001
 None - OutsideSN       -2.2979 0.150 831 -15.306  <.0001
 None - InsideSN        -4.5000 0.150 831 -29.975  <.0001
 OutsideSN - InsideSN   -2.2021 0.150 831 -14.669  <.0001

InfoAcq_f = OverheardUnIn:
 contrast              estimate    SE  df t.ratio p.value
 Unknown - None          1.4433 0.148 831   9.766  <.0001
 Unknown - OutsideSN    -0.4948 0.148 831  -3.348  0.0047
 Unknown - InsideSN     -2.2371 0.148 831 -15.138  <.0001
 None - OutsideSN       -1.9381 0.148 831 -13.115  <.0001
 None - InsideSN        -3.6804 0.148 831 -24.904  <.0001
 OutsideSN - InsideSN   -1.7423 0.148 831 -11.789  <.0001

InfoAcq_f = OverheardIn:
 contrast              estimate    SE  df t.ratio p.value
 Unknown - None          0.7528 0.154 831   4.879  <.0001
 Unknown - OutsideSN    -0.0337 0.154 831  -0.218  0.9963
 Unknown - InsideSN     -0.9551 0.154 831  -6.190  <.0001
 None - OutsideSN       -0.7865 0.154 831  -5.098  <.0001
 None - InsideSN        -1.7079 0.154 831 -11.070  <.0001
 OutsideSN - InsideSN   -0.9213 0.154 831  -5.972  <.0001

Degrees-of-freedom method: kenward-roger
P value adjustment: tukey method for comparing a family of 4 estimates
```

5. Linear Mixed Effects Model: Violation of Privacy

```
>m4<-lmerTest::lmer(Violate~InfoTrans_f*InfoAcq_f+(1|Response_ID),data=d)
> sum_m4<-summary(m4)
> print(sum_m4)

Linear mixed model fit by REML. t-tests use Satterthwaite's method
['lmerModLmerTest']
Formula: Violate ~ InfoTrans_f * InfoAcq_f + (1 | Response_ID)
   Data: d

REML criterion at convergence: 2243.1
```

```
Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.0635 -0.5369  0.0680  0.6649  3.3968

Random effects:
 Groups      Name        Variance Std.Dev.
 Response_ID (Intercept) 0.2004   0.4477
 Residual                0.3060   0.5532
Number of obs: 1120, groups:  Response_ID, 280

Fixed effects:
                                             Estimate Std. Error        df t
value Pr(>|t|)
(Intercept)                                   1.53191    0.07340 753.79465
20.871  < 2e-16 ***
InfoTrans_fNone                              -0.41489    0.08069 831.00000  -
5.142 3.39e-07 ***
InfoTrans_fOutsideSN                          1.01064    0.08069 831.00000
12.525  < 2e-16 ***
InfoTrans_fInsideSN                           2.02128    0.08069 831.00000
25.050  < 2e-16 ***
InfoAcq_fOverheardUnIn                        0.80829    0.10300 753.79465
7.848 1.45e-14 ***
InfoAcq_fOverheardIn                          2.18719    0.10525 753.79465
20.780  < 2e-16 ***
InfoTrans_fNone:InfoAcq_fOverheardUnIn       -0.20366    0.11323 831.00000  -
1.799  0.07243 .
InfoTrans_fOutsideSN:InfoAcq_fOverheardUnIn  -0.37146    0.11323 831.00000  -
3.281  0.00108 **
InfoTrans_fInsideSN:InfoAcq_fOverheardUnIn   -0.61921    0.11323 831.00000  -
5.469 6.00e-08 ***
InfoTrans_fNone:InfoAcq_fOverheardIn          0.10029    0.11570 831.00000
0.867  0.38633
InfoTrans_fOutsideSN:InfoAcq_fOverheardIn    -1.05558    0.11570 831.00000  -
9.123  < 2e-16 ***
InfoTrans_fInsideSN:InfoAcq_fOverheardIn     -1.79656    0.11570 831.00000 -
15.527  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
             (Intr) InfT_N InT_OSN InT_ISN IA_OUI InA_OI IT_N:IA_OU
IT_OSN:IA_OU IT_ISN:IA_OU IT_N:IA_OI
InfTrns_fNn  -0.550
InfTrns_OSN  -0.550  0.500
InfTrns_ISN  -0.550  0.500  0.500
InfAcq_fOUI  -0.713  0.392  0.392   0.392
InfAcq_fOvI  -0.697  0.383  0.383   0.383   0.497
IT_N:IA_OUI   0.392 -0.713 -0.356  -0.356  -0.550 -0.273
IT_OSN:IA_OU  0.392 -0.356 -0.713  -0.356  -0.550 -0.273  0.500
IT_ISN:IA_OU  0.392 -0.356 -0.356  -0.713  -0.550 -0.273  0.500      0.500
InT_N:IA_OI   0.383 -0.697 -0.349  -0.349  -0.273 -0.550  0.497      0.248
0.248
IT_OSN:IA_OI  0.383 -0.349 -0.697  -0.349  -0.273 -0.550  0.248      0.497
0.248        0.500
```

```
IT_ISN:IA_OI  0.383 -0.349 -0.349  -0.697  -0.273 -0.550  0.248      0.248
0.497        0.500
             IT_OSN:IA_OI
InfTrns_fNn
InfTrns_OSN
InfTrns_ISN
InfAcq_fOUI
InfAcq_fOvI
IT_N:IA_OUI
IT_OSN:IA_OU
IT_ISN:IA_OU
InT_N:IA_OI
IT_OSN:IA_OI
IT_ISN:IA_OI  0.500

> confint(m4)
Computing profile confidence intervals ...
                                                2.5 %      97.5 %
.sig01                                      0.3959461  0.49961935
.sigma                                      0.5249125  0.57760624
(Intercept)                                 1.3886436  1.67518620
InfoTrans_fNone                            -0.5723732 -0.25741405
InfoTrans_fOutsideSN                        0.8531587  1.16811787
InfoTrans_fInsideSN                         1.8637970  2.17875617
InfoAcq_fOverheardUnIn                      0.6072478  1.00933480
InfoAcq_fOverheardIn                        1.9817440  2.39262849
InfoTrans_fNone:InfoAcq_fOverheardUnIn     -0.4246441  0.01731797
InfoTrans_fOutsideSN:InfoAcq_fOverheardUnIn -0.5924441 -0.15048199
InfoTrans_fInsideSN:InfoAcq_fOverheardUnIn -0.8401958 -0.39823369
InfoTrans_fNone:InfoAcq_fOverheardIn       -0.1255292  0.32610290
InfoTrans_fOutsideSN:InfoAcq_fOverheardIn  -1.2813981 -0.82976609
InfoTrans_fInsideSN:InfoAcq_fOverheardIn   -2.0223735 -1.57074147

> anova(m4)
Type III Analysis of Variance Table with Satterthwaite's method
                      Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
InfoTrans_f           431.56 143.854     3   831 470.096 < 2.2e-16 ***
InfoAcq_f             116.91  58.457     2   277 191.030 < 2.2e-16 ***
InfoTrans_f:InfoAcq_f 121.50  20.250     6   831  66.174 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> BIC(m4)
[1] 2341.415
```

5a. Estimated Marginal Means of Violation of Privacy, Averaging over Manner of Acquisition

```
> emm_m4.1 <- emmeans(m4, specs=c("InfoTrans_f"))
NOTE: Results may be misleading due to involvement in interactions
> emm_m4.1
 InfoTrans_f emmean     SE  df lower.CL upper.CL
 Unknown       2.53 0.0426 754     2.45     2.61
 None          2.08 0.0426 754     2.00     2.16
 OutsideSN     3.07 0.0426 754     2.98     3.15
 InsideSN      3.75 0.0426 754     3.66     3.83
```

```
Results are averaged over the levels of: InfoAcq_f
Degrees-of-freedom method: kenward-roger
Confidence level used: 0.95

> contrast(emm_m4.1, method="pairwise",simple="InfoTrans_f")
 contrast               estimate     SE  df t.ratio p.value
 Unknown - None            0.449 0.0468 831   9.605  <.0001
 Unknown - OutsideSN      -0.535 0.0468 831 -11.435  <.0001
 Unknown - InsideSN       -1.216 0.0468 831 -25.993  <.0001
 None - OutsideSN         -0.984 0.0468 831 -21.040  <.0001
 None - InsideSN          -1.665 0.0468 831 -35.599  <.0001
 OutsideSN - InsideSN     -0.681 0.0468 831 -14.558  <.0001

Results are averaged over the levels of: InfoAcq_f
Degrees-of-freedom method: kenward-roger
P value adjustment: tukey method for comparing a family of 4 estimates
```

5b. Estimated Marginal Means of Violation of Privacy, Specifying Manner of Acquisition

```
> emm_m4 <- emmeans(m4, specs=c("InfoTrans_f", "InfoAcq_f"))
> emm_m4
 InfoTrans_f InfoAcq_f      emmean     SE  df lower.CL upper.CL
 Unknown     Disclosed        1.53 0.0734 754    1.388     1.68
 None        Disclosed        1.12 0.0734 754    0.973     1.26
 OutsideSN   Disclosed        2.54 0.0734 754    2.398     2.69
 InsideSN    Disclosed        3.55 0.0734 754    3.409     3.70
 Unknown     OverheardUnIn    2.34 0.0723 754    2.198     2.48
 None        OverheardUnIn    1.72 0.0723 754    1.580     1.86
 OutsideSN   OverheardUnIn    2.98 0.0723 754    2.838     3.12
 InsideSN    OverheardUnIn    3.74 0.0723 754    3.600     3.88
 Unknown     OverheardIn      3.72 0.0754 754    3.571     3.87
 None        OverheardIn      3.40 0.0754 754    3.256     3.55
 OutsideSN   OverheardIn      3.67 0.0754 754    3.526     3.82
 InsideSN    OverheardIn      3.94 0.0754 754    3.796     4.09

Degrees-of-freedom method: kenward-roger
Confidence level used: 0.95

> contrast(emm_m4, method="pairwise",simple="InfoTrans_f")
InfoAcq_f = Disclosed:
 contrast               estimate     SE  df t.ratio p.value
 Unknown - None           0.4149 0.0807 831   5.142  <.0001
 Unknown - OutsideSN     -1.0106 0.0807 831 -12.525  <.0001
 Unknown - InsideSN      -2.0213 0.0807 831 -25.050  <.0001
 None - OutsideSN        -1.4255 0.0807 831 -17.667  <.0001
 None - InsideSN         -2.4362 0.0807 831 -30.192  <.0001
 OutsideSN - InsideSN    -1.0106 0.0807 831 -12.525  <.0001

InfoAcq_f = OverheardUnIn:
 contrast               estimate     SE  df t.ratio p.value
 Unknown - None           0.6186 0.0794 831   7.787  <.0001
 Unknown - OutsideSN     -0.6392 0.0794 831  -8.047  <.0001
 Unknown - InsideSN      -1.4021 0.0794 831 -17.651  <.0001
 None - OutsideSN        -1.2577 0.0794 831 -15.834  <.0001
 None - InsideSN         -2.0206 0.0794 831 -25.438  <.0001
 OutsideSN - InsideSN    -0.7629 0.0794 831  -9.604  <.0001
```

```
InfoAcq_f = OverheardIn:
 contrast              estimate     SE  df t.ratio p.value
 Unknown - None          0.3146 0.0829 831   3.794  0.0009
 Unknown - OutsideSN     0.0449 0.0829 831   0.542  0.9487
 Unknown - InsideSN     -0.2247 0.0829 831  -2.710  0.0346
 None - OutsideSN       -0.2697 0.0829 831  -3.252  0.0065
 None - InsideSN        -0.5393 0.0829 831  -6.504  <.0001
 OutsideSN - InsideSN  -0.2697 0.0829 831  -3.252  0.0065

Degrees-of-freedom method: kenward-roger
P value adjustment: tukey method for comparing a family of 4 estimates
```

Bibliography

Acquisti, A., Brandimarte, L., & Hancock, J. (2022). How privacy's past may shape its future. *Science*, *375*(6578), 270–272. https://doi.org/10.1126/science.abj0826

Acquisti, A., Brandimarte, L., & Loewenstein, G. (2015). Privacy and human behavior in the age of information. *Science*, *347*(6221), 509–514. https://doi.org/10.1126/science.aaa1465

Barrett, H. C., Bolyanatz, A., Crittenden, A. N., Fessler, D. M. T., Fitzpatrick, S., Gurven, M., Henrich, J., Kanovsky, M., Kushnick, G., Pisor, A., Scelza, B. A., Stich, S., Von Rueden, C., Zhao, W., & Laurence, S. (2016). Small-scale societies exhibit fundamental variation in the role of intentions in moral judgment. *Proceedings of the National Academy of Sciences*, *113*(17), 4688–4693. https://doi.org/10.1073/pnas.1522070113

Barth, S., & de Jong, M. D. T. (2017). The privacy paradox – Investigating discrepancies between expressed privacy concerns and actual online behavior – A systematic literature review. *Telematics and Informatics*, *34*(7), 1038–1058. https://doi.org/10.1016/j.tele.2017.04.013

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*, 1–48. https://doi.org/10.18637/jss.v067.i01

Buskell, A. (2017). What are cultural attractors? *Biology & Philosophy*, *32*(3), 377–394. https://doi.org/10.1007/s10539-017-9570-6

Carter, J., Lyons, N. J., Cole, H. L., & Goldsmith, A. R. (2008). Subtle cues of predation risk: Starlings respond to a predator's direction of eye-gaze. *Proceedings of the Royal Society B: Biological Sciences*, *275*(1644), 1709–1715. https://doi.org/10.1098/rspb.2008.0095

Dinev, T., & Hart, P. (2006). An Extended Privacy Calculus Model for E-Commerce Transactions. *Information Systems Research*, *17*(1), 61–80.

Hare, B., Call, J., Agnetta, B., & Tomasello, M. (2000). Chimpanzees know what conspecifics do and do not see. *Animal Behaviour*, *59*(4), 771–785. https://doi.org/10.1006/anbe.1999.1377

Hess, N. H., & Hagen, E. H. (2023). The impact of gossip, reputation, and context on resource transfers among Aka hunter-gatherers, Ngandu horticulturalists, and MTurkers. *Evolution and Human Behavior*, *44*(5), 442–453. https://doi.org/10.1016/j.evolhumbehav.2023.02.013

Kaplan, H., Hill, K., Lancaster, J., & Hurtado, A. M. (2000). A theory of human life history evolution: Diet, intelligence, and longevity. *Evolutionary Anthropology*, *9*(4), 156–185.

Kokolakis, S. (2017). Privacy attitudes and privacy behaviour: A review of current research on the privacy paradox phenomenon. *Computers & Security*, *64*, 122–134. https://doi.org/10.1016/j.cose.2015.07.002

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software*, *82*, 1–26. https://doi.org/10.18637/jss.v082.i13

Lind, P. G., da Silva, L. R., Andrade, J. S., & Herrmann, H. J. (2007). Spreading gossip in social networks. *Physical Review E*, *76*(3), 036117. https://doi.org/10.1103/PhysRevE.76.036117

McElreath, R., Boyd, R., & Richerson, P. (2003). Shared Norms and the Evolution of Ethnic Markers. *Current Anthropology*. https://doi.org/10.1086/345689

Miritello, G., Moro, E., & Lara, R. (2011). Dynamical strength of social ties in information spreading. *Physical Review E*, *83*(4), 045102. https://doi.org/10.1103/PhysRevE.83.045102

Richerson, P. J., & Boyd, R. (2006). *Not By Genes Alone: How Culture Transformed Human Evolution*. University of Chicago Press.

Sperber, D. (1996). *Explaining culture: A naturalistic approach*. Oxford Blackwell.