Privacy Decision Making: The Brain Approach

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Functional magnetic resonance imaging tools develop neurobiological evidence of human brain reactions to privacy risks. Our results indicate that privacy decisions are more affective cognitive than purely cognitive, as assumed in the existing affective-computing models for privacy decision making.

Most current research in information privacy focuses on providing confidential data that develops new privacy-enhancing technologies, with customer data encryption often presented as a potential solution. At the same time, many of these technologies are not being effectively utilized because of problems that are endemic to human judgment under risk and uncertainty. The vast majority of the existing models and products, which are validated by paper-and-pencil, web-based surveys/interviews, are mainly based on a limited number of documented incidents as well as questionable assumptions about user intent and behavior. For example, they assume that online users act as rational economic agents when making privacy decisions and always choose the option with the maximum utility in a unitary cognitive process.

In our research, we answer fundamental questions about online privacy and privacy decision making: Are privacy decisions purely cognitive, and can they adequately be described by a rational theory of decision making, or do they reflect the engagement of affective (emotion) systems in the human brain?

We take a fundamentally different approach to privacy research, and, to the best of our knowledge, we investigate, for the first time, whether or not the human brain's reactions to privacy risks conform to the existing cognitive models of privacy decision making. We use functional magnetic resonance imaging (fMRI)

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tools to visualize changes in oxygen utilization (or activation, i.e., neural activity) in privacy decisions. This is the first step in forming a new discipline—neuroprivacy.

In this article, following a brief background, we explain how we use brain-imaging tools for the neurobiological investigation of human brain reactions to privacy risks. Then, based on our results, we posit that the human brain, in privacy decision making, follows a dual process. We argue that "affect" should be recognized in privacy-decision analysis and that the affective substrates of behavioral economic theories make them more practical than the expected utility theory in describing privacy decisions.

COMPUTATIONAL MODELS OF PRIVACY DECISIONS

Prior to the popularity of the Internet, the computer science community focused much of its research on privacy. The majority of this research, however, considered only protecting confidentiality (data anonymization and access control policy, for example).

Despite the fact that computer science has been recognized as one of the fastest growing disciplines, the computational models of privacy decisions are still derived from traditional decision-making models and expected utility theory. That is, they are based on von Neumann and Morgenstern's landmark 1953 theory of games and economic behavior.[1] According to these models, online users are considered rational economic agents who follow a unitary cognitive process in their privacy decisions. In rational choice and expected utility theory, affect plays little or no role in the decision process. In other words, people's preferences are not supposed to be influenced by the social structures in which they engage.

This approach has been followed even in recent and popular computational models of privacy, such as differential privacy.[2] In this school of thought, affect is not even considered in the task environment, which includes a set of players, types, outcomes, reactions, a utility function, and rational agents who play to maximize their own utility. As such, "…every preference relation over mechanisms that satisfies reasonable axioms (encoding 'rationality') can be modeled via expected utility, just as [the authors] propose. This theorem justifies priors to express a rational user's tradeoff over possible inputs."[3] However, the results of many experimental studies indicate that, although a majority of people claim to be very concerned about their privacy, they do not consistently take actions to protect it.[4] These inconsistencies violate the assumptions of the expected utility theory and encourage consideration of more realistic models of privacy decision making.

fMRI AS A WINDOW TO PRIVACY RISKS

To investigate privacy decisions, hypotheses are typically developed and then tested using collected data from paper-and-pencil, web-based surveys/interviews. However, recent advances in the spatial and temporal resolution of brain-imaging techniques have enabled researchers to track changes in the cortical and subcortical activity of humans as they make decisions.[5] Specifically, event-related fMRI allows investigators to visualize changes in oxygen utilization in deep subcortical regions as small as 2 mm in mere seconds. These advances allow investigators to examine and compare brain activation before and during privacy decision making. These developments create new and unique theoretical opportunities for investigating neural correlations of privacy risks as well as practical opportunities to predict individuals' upcoming privacy decisions. There is strong empirical evidence that the blood-oxygen-level-dependent (BOLD) signals in fMRI are highly correlated with neuronal activities.[6] fMRI has had a major influence on validating various theories in different disciplines (economics, for example) and has created new horizons for understanding human behavior. But, to the best of our knowledge, it has not yet been used by researchers in the realm of privacy.

MATERIALS AND METHODS

After receiving an institutional review board approval (the proper authorization for carrying out human-involved research), we conducted a set of fMRI experiments on 14 human subjects. All of the subjects were right-handed and had no history of psychiatric or neurological illness. In these experiments, participants answered yes or no to more than 60 privacy-related questions (for example, Do you know if school system administrators can read your emails?), and 60 nonprivacy-related questions (Do you prefer Pepsi to Coke?). The privacy-related and nonprivacy-related questions were asked in random order. We used E-Prime to present the experiment and the fMRI of the Brain (FMRIB) Software Library (FSL) to analyze the functional and structural fMRI data. A summary of the sequence details and data analysis is provided in the following section. Participants were given 4 s to respond to each question, using an MRI-compatible keypad, operated with their right hand. The entire scanning session per participant lasted approximately 50 min.

Sequence

All of the MRI data were acquired using a 3-T Siemens Trio MRI scanner with a 12-channel head coil. T2*-sensitive functional imaging was performed using a gradient-echo, echo-planar imaging sequence [time to echo (TE) = 30 ms, time to repetition (TR) = 2,000 ms; 90° flip angle; field of view (FOV) = 204; and a 68 × 68 in-plane matrix, a 37-axial, and a 3-mm-thick slice with a 10% slice gap; for B0 unwarping, echo spacing was 0.49 ms and phase encoding was A> P ("y-")] to obtain functional images. To obtain structural 3D volume, T1-weighted images were acquired using a magnetization-prepared rapid acquisition gradient echo sequence (inversion time = 85 ms, TR = 2,250 ms between shots, TE = 3.98 ms; 90° flip angle; FOV = 256 × 256 mm; 176 1-mm sagittal slices; and a 256 × 256 matrix).

Using fMRI (first with a phase-region expanding labeler for unwrapping discrete estimates, then FMRIB's utility for geometrically unwarping echoplanar imaging), time-series statistical analysis was performed using a general linear model with local autocorrelation correction (FMRIB's improved linear model). The fMRI data for each participant were analyzed in native space and coregistered to standard Montreal Neurological Institute (MNI) space using an average template created from 152, first with an initial affine registration to the high-resolution structural space and then from the high-resolution structural space to standard MNI space using nonlinear registration.

Higher-level (group) analyses were carried out using a Bayesian mixed-effects analysis. Neural activation was indirectly measured as localized BOLD signal intensity during each condition compared to an implicitly modeled baseline (between stimuli rest) to determine the regions of activation associated with various levels of risk. Z (Gaussianized T) statistic images were produced by applying a cluster threshold of $Z > 2.0$ and a significance threshold of $P = 0.05$. Binarized masks of significant clusters surviving these thresholding and correction steps were created and passed to the command line atlasquery function of the FSL. Cluster peaks and anatomical regions within the volume were localized in MNI152 space using the Jeulich histological atlas, which is supplied in the FSL 5.0 distribution. For illustrative purposes, the mean statistical maps were overlaid onto a standard brain template (cvs_avg_inMNI152) using FreeSurfer 5.3.0 (http://surfer.nmr.mgh.harvard.edu/).

RESULTS

Figure 1 captures the fMRI results and illustrates the brain regions that have increased activity. Our results show significant differences among brain activities in response to privacy compared with nonprivacy-related questions. We found that the brain regions with increased activity in the privacy state are mainly located in the limbic system. We also found some limited activity in the higher cognitive processing area of the brain, including the inferior parietal lobule (IPL). We list the brain activity of our subjects under three main areas.

1. *Limbic system*: This area is primarily concerned with behaviors governed by emotional responses. Specific regions of the limbic system with increased activity in the brains of our participants include
   - the amygdala, which plays a key role in emotional information processing, such as anger, distrust, negative emotions, pleasure, and fear. It is also involved in regulating both positive and negative emotions.
   - the hippocampus, which processes information to be stored in long-term memory. Two important parts of the limbic system were not active in the privacy decisions of our participants: 1) the anterior cingulate cortex, which is the part of the brain that is vital in cognitive activities (decision making and reward anticipation), and 2) the nucleus accumbens, which provides a link between the limbic system (emotions regulator) and the central gray nuclei that help with reasoning and planning. This area is normally active in different circumstances such as aversive, novel, unexpected, or intense stimuli. This is particularly important because previous studies have indicated that there is a correlation between an individual's risk avoidance and the brain activation in the nucleus accumbens.[6]
2. *Higher cognitive processing center in the brain cortex*: We observed increased activity in the IPL in response to privacy questions versus nonprivacy questions. The IPL plays a key role in various cognitive functions, including decision

making under risk and uncertainty and action processing.
3. *Thalamus area*: The left and right lateral geniculate body (LGN) as well as the left and right medial geniculate body showed increased activity in our experiments. LGN is traditionally viewed as the gateway to the visual cortex; however, it may also serve as a gatekeeper for controlling attentional response gain. Attention modulates neural activity in the human LGN in several ways, including enhanced neural responses to attended stimuli, attenuated responses to ignored stimuli, and increased baseline activity in the absence of visual stimulation.

Our results suggest that privacy risks cause the activation of major areas of the limbic system including the amygdala, which is primarily concerned with behaviors governed by emotional responses. The limbic system exerts influence throughout the brain via major neurotransmitters (the most important being midbrain dopaminergic projections), which synapse onto the regions involved in emotional possessing such as the amygdala and the cingulate gyrus. They both showed increased activity in the brains of our participants in response to privacy questions.

Our results also suggest the involvement of emotional memories for privacy decision making. The amygdala and hippocampal complex, which showed increased activity, are located in the medial temporal lobe structures and linked to two independent memory systems, each with unique characteristic functions.

In our results, the involvement of emotions and emotional memories in privacy decision-making processes is particularly important. Emotional memories allow for the learning of secondary emotions as generalizations of primary ones; in fact, they serve as markers or biasing mechanisms that influence what decisions are made and how the agent behaves. Previous research has shown several frontal and parietal regions that are more

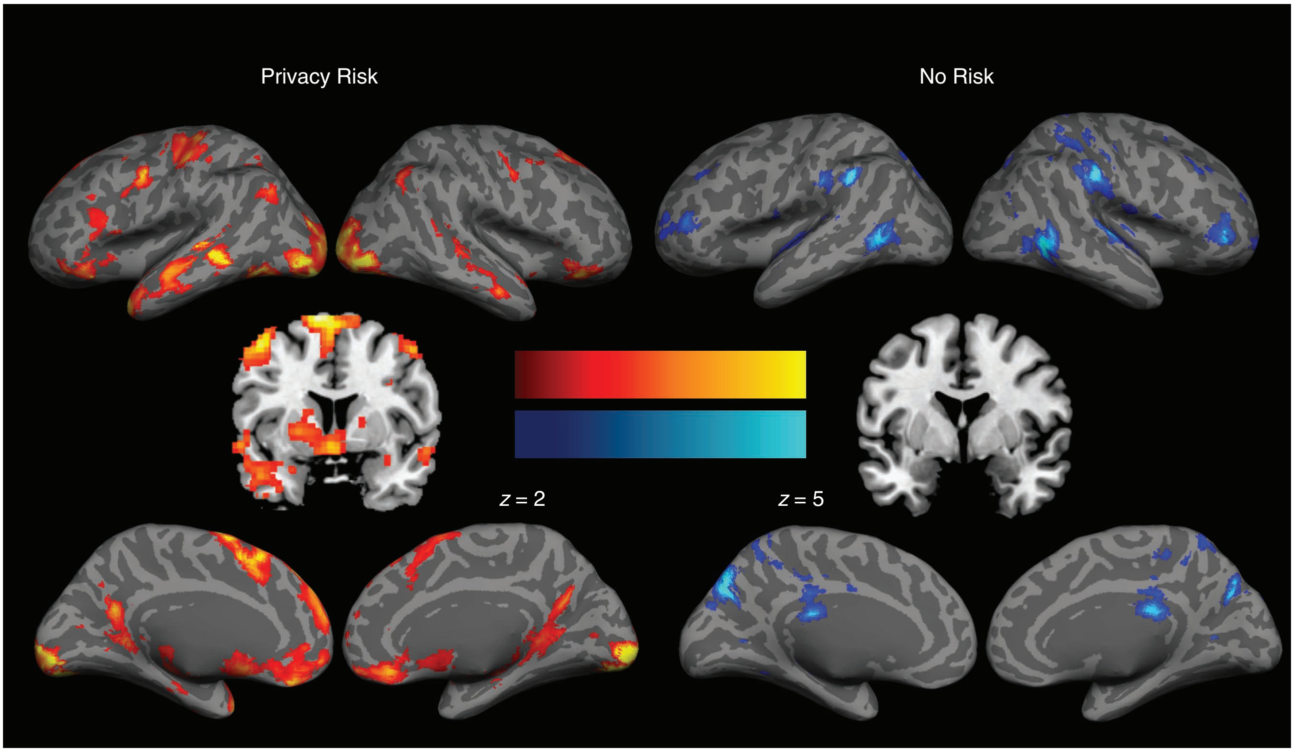

FIGURE 1. The fMRI results that show the whole-brain analysis of parametric responses to privacy-risk and no-risk activities (a higher z score means activation is more likely).

active during uncertain as opposed to certain decision making.[7] However, our results showed increased activity in the IPL in response to privacy versus nonprivacy questions. This is considerably different from the regions that normally light up when cognitive questions are answered.

A DUAL-PROCESS FRAMEWORK FOR PRIVACY DECISION MAKING

Our results support the dual-system operation that has been applied in psychology and business and marketing research and drives privacy decisions. Kahneman referred to these systems as *system 1* and *system 2*.[8] Based on our results, we posit that privacy decisions are the outcomes of collaboration and competition between these two systems:

1. *System 1* (*affective*) operates automatically and quickly, with little or no effort and no sense of voluntary control.
2. *System 2* (*cognitive*) allocates attention to the effortful mental activities that demand it, including computations. The operation of system 2 is often associated with subjective experiences and concentration.

As shown in Figure 2, we propose a formal dual-process model in which a privacy decision is the joint product of an affective system that encompasses emotions (system 1) and a cognitive system that assesses options in a consequentialist fashion (system 2).

Systems 1 and 2 are influenced by environmental stimuli. Perhaps most important is the temporal proximity of reward and cost stimuli. This concept has been studied by behavioral economists under the economics of immediate gratification and has been considered in privacy research.[9] Affective motivations are intense when rewards and punishments are immediate but much less intense when they are temporally remote. Cognition and deliberation are, in contrast, much less sensitive to immediacy.

From a formal perspective, following behavioral economics proposals,[10] we can develop two objective functions that operate simultaneously. A stimulus, $s \in S$, activates affective and cognitive systems. That is, it can activate an affective state $a(s)$ and a cognitive state $c(s)$; the set of intuitive and deliberate states could themselves be subsets of S. Now, the problem is how to predict when a user will choose x from a set of $X \subseteq \mathbb{R}$, given that the two systems may have different objective functions and neither fully dominates the other. We can define the objective function of the affective system by U^a [x and $a(s)$], which is maximized at $x^a \in X$. Similarly, we can define the objective function of the deliberate system as U^c [x, $a(s)$, and $c(s)$], which is maximized at $x^c \in X$. Figure 2 illustrates these processes.

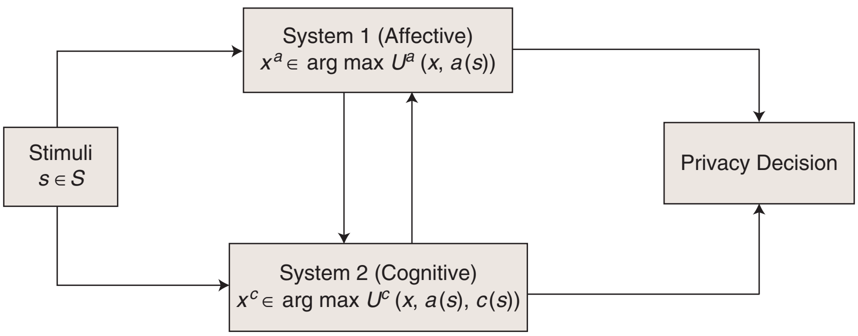

FIGURE 2. A simplified framework that depicts the dual process in privacy decision making.

In the following section, we present an example of how this framework can be used in capturing the dual process. Specifically, we explain how the value and weighting functions of prospect theory[11] and their parameters (e.g., α, β, λ, and γ) can show the intensity of affect in privacy decisions.

The example of prospect theory

The Nobel Prize-winning prospect theory is an example of decision theories that capture affective-cognitive processes in privacy decisions. Prospect theory, unlike expected utility theory,[1] not only assumes a pure cognitive process in human decision process but captures affective processes as well. For example, it captures loss aversion; people strongly prefer avoiding losses over acquiring gains.

Prospect theory describes the process of decision making in two phases: editing and evaluation. In the editing phase, the decision maker edits the options to facilitate the assessment. In prospect theory, the editing and evaluation phases are captured by value and weighting functions; the value of the prospect (x, p) is given by $W(p)V(x)$, where W is a nonlinear weighting function, p is the probability of gains/losses, and V is the value function for gains and losses. The first scale, W, associates with each probability p a decision weight $W(p)$, which reflects the impact of p on the overall value of the prospect. However, W is not a probability measure, and $W(p) + W(1 - p)$ is typically less than unity. Prospect theory describes the outcomes as gains or losses compared to some reference point. In the evaluation phase, the decision maker assesses the edited options. For example, should I disclose my personal information to the grocery store to receive a loyalty card and avoid a US$5 loss when I shop today? The function of the editing phase is to organize and reformulate the options so as to simplify subsequent evaluations and choices. Editing consists of applying several operations that transform the outcomes and probabilities associated with the prospects offered. Following the editing phase, the decision maker evaluates each of the edited prospects and chooses the prospect of highest value.

The value function assigns to each outcome x a number $V(x)$ that reflects the subjective value of that outcome. Outcomes are defined relative to a reference point, which serves as the zero point of the value scale. Hence, $V(x)$ measures the value of deviations from that reference point, i.e., gains and losses. The S-shape prospect theory value function [Figure 3(a)] replaces the utility function of expected utility. The value function's degree of curvature represents a decision maker's sensitivity to an increasing number of units gained or lost. The value function has a kink at the reference point so that it is steeper to the left of the origin and can capture the fact that losses loom larger than gains. This feature can explain some privacy behaviors that cannot be explained by expected utility theory. For example, situations where giving up information leads to a loss of privacy are weighted more intensely than the gain from monetary compensation, and vice versa.

The prospect theory value function can be represented as

$$V(x) = \begin{cases} x^{a} & x \geq 0 \\ -\lambda(-x)^{\beta} & x < 0 \end{cases}. \tag{1}$$

The value function presents two drifts: one associated with the affective system and one associated with the cognitive system. The value function can be used to calculate the drift rates for both systems but allow for different parameter values (i.e., α, β, and λ) for the two systems. α and $\beta > 0$ measure the curvature of the value function for gains and losses, respectively, and λ is the coefficient of loss aversion. Thus, the value function for gains (losses) is increasingly concave (convex) for smaller values of α and $\beta < 1$, and loss aversion is more pronounced for larger values of $\lambda > 1$.

The weighting function combines two elements: 1) the level of probability weight is a way of expressing risk tastes, and 2) the curvature in $W(p)$ captures how affective people are to differences in probabilities. Rottenstreich and Hsee report that the curvature of the weighting function seems to be more pronounced for more "affect-rich" consequences.[12] For example, disclosure of secrets to coworkers could be more affective than disclosure to close friends. A hypothetical weighting function [Figure 3(b)] can be represented as

$$W(p) = \frac{\delta p^{\Upsilon}}{\delta p^{\Upsilon} + (1 - p)^{\Upsilon}}. \tag{2}$$

For weighting functions, $\delta > 0$ measures the elevation of the weighting function, and $\Upsilon > 0$ measures its degree of curvature. The weighting function is more elevated (exhibits less overall risk aversion for gains and more overall risk aversion for losses) as δ increases and is more curved (exhibits more rapidly diminishing sensitivity to probabilities around the boundaries of 0 and 1) as $\Upsilon < 1$ decreases (the function exhibits an S-shaped pattern that is more pronounced for larger values of $\Upsilon > 1$.

One important aspect of prospect theory is that people evaluate the outcome of decisions based on a flexible reference point rather than absolute levels. Several studies using fMRI have provided support for this prediction and demonstrate that the neural

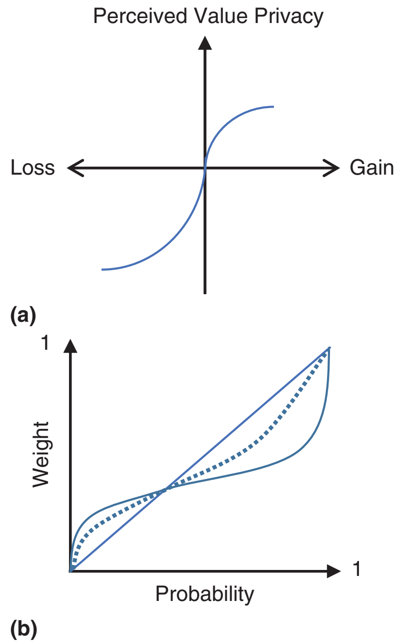

FIGURE 3. (a) The hypothetical value function in prospect theory; outcomes are defined relative to a reference point. (b) The hypothetical weighting functions in prospect theory; no affect (a straight line), affect poor (a dotted curve), and more affective or affect rich (a solid curve).

signatures of reward are determined by the value of the outcome relative to the range of possible outcomes rather than the objective value of the outcome itself. Additionally, a growing body of evidence suggests that decision making under risk is mediated by a network of cortical and limbic structures devoted to processing sensory, cognitive, and affective information as well as widely projecting neuromodulator systems.[5,6]

Prospect theory and neural representations of utility

Our fMRI results indicate strong support for the role of system 1 (affective operations, see Figure 2), which relies on the amygdala and hippocampus in the limbic system of the human brain, versus system 2 (cognitive operations), which relies on brain cortices in the IPL. The limbic system is a set of structures in the brain that deal with emotions and memory. It regulates autonomic or endocrine function in response to emotional stimuli and also is involved in reinforcing behavior. Neurotransmitters, such as serotonin and dopamine, are chemical messengers that send signals across the network. Brain regions receive these signals, which results in recognizing situations, assigning them an emotional value to guide behavior, and making split-second risk/reward assessments. Such results cannot be explained by expected utility theory, which only considers the role of system-2 operations and gives little or no consideration to the role of system-1 operations in decision processes. That is, the expected utility theory cannot realistically describe the brain's approach to privacy risks and capture "utility" as perceived by the decision maker. Then, the question is as follows: What is utility in the eye of an individual in a privacy-related decision, and how can we capture it?

In computer science and engineering, utility is introduced as the mathematical treatment of "preferred" outcomes. Emotional states (for example, happiness) are not part of the equation because they sound insufficiently scientific, so economists and computer scientists use the term *utility*, instead.[13] This perspective can safely be equated with the von Neumann–Morgenstern perspective on "decision utility," i.e., weight of potential outcomes in decisions (wantability). However, many situations, such as the privacy decisions investigated in this study, are more focused on the immediate experiences (pain or pleasure) that correspond to "experienced utility" (likability). These are distinct concepts of utility. Wanting to work in a profession without enjoying the profession is a simple example of the difference between wantability and likability (decision utility and experienced utility). Previous neuroscience research has identified different brain mechanisms for decision utility and experienced utility,[14] and our fMRI results are more supportive of the brain's mechanism for experienced utility than decision utility in privacy decisions.

Our results also support that the affective substrates of prospect theory, and its ability to capture both experienced utility and decision utility, make it a more realistic decision theory than the expected utility theory when describing privacy decision making.

Curvature of the value and weighting functions. In prospect theory, the curvature degree of the value function represents a decision maker's sensitivity to increasing units lost (or gained). In other words, the value function exhibits greater curvature (that is, a lower slope above a minimum number of units gained or lost) for consequences that are more "affect rich" versus the consequences that are "affect poor." As noted previously, the disclosure of a personal secret to family members could be affect poor, whereas disclosure of the same secret to coworkers could be affect rich. A similar argument can be made about the curvature of the weighting function and how it captures the nonlinearity reflected in an individuals' decisions.

Reference dependence. In prospect theory, the concept of reference dependence and change in the reference point reflects the difference between the decision utility and the experienced utility. Using prospect theory's utility function as a representation of the decision utility, the reference point is at the inflection of the function, and its decision utility is zero. A neutral reference point serves as the basis for the planned choice; that is, zero payoffs are assigned zero. The reference-dependent characteristics utilize the prospect theory value function as a representation of the experienced utility as well.[15]

The brain's reaction to privacy risks found in our study and the highly social nature of the brain require recognition of affect in privacy-decision analysis. Affective reactions to outcomes differ from the utilities associated with outcomes. As such, minimizing subjective expected pain of privacy loss is not the same as the "minimal notion of privacy,"[2] which is assumed to be independent of beliefs and monotonically related to monetary outcomes as inferred from choice, in the spirit of Neumann and Morgenstern.[1]

The existing computational models of privacy decisions ignore the idea that such decisions may not emerge from only a unitary process but rather from interactions among distinguishable sets of processes. However, our results, consistent with the findings of neuroeconomists and neuropsychologists, indicate that reactions to privacy risks involve an interaction among multiple subsystems governed by different parameters and possibly even different principles (for example, cognitive and affective processes). That is, the human brain's role in privacy decision making follows a dual process.

To develop realistic tools, privacy-enhancing technology developers and the privacy research community must acknowledge the role of affect in privacy behaviors. Our results indicate that, in developing these tools, decision theories that can capture affective-cognitive processes (e.g., prospect theory) are more appropriate than classic decision theories (e.g., expected utility theory), which assume that humans always choose option with the maximum utility and that their decisions are purely cognitive.

In this research, we used fMRI to investigate responses to privacy risks in which particular regions of the brain are expected to light up, indicating increased flow of oxygen and heightened neural activity. This is the first step in forming a new discipline that deals with the neural correlation of privacy decisions, which we call *neuroprivacy*. We hope that our work inspires the privacy research community to contribute to this discipline by studying the connections between how the mind/brain works, the internal order of the mind, and privacy behavior in 1) individual decision making, 2) social exchange, and 3) institutions, such as the marketplace. Neuroprivacy is driven primarily by machines used for brain imaging, a technology sure to become more sophisticated, offering much promise for changing the way we think about privacy in online environments and human sociality. Neuroprivacy uses neuroscience to inform privacy research, in a way similar to how neuroeconomics informs economics.

The long-term goal of neuroprivacy is to provide more than a privacy map of the mind. By tracking what parts of the brain are activated by different tasks and especially by looking for the overlap among diverse tasks, we can understand how the brain's parts interact in circuitry and therefore, how the brain executes a privacy decision. For example, because different parts of the brain are more or less associated with affective or cognitive processing, imaging people while they are doing privacy-related tasks provides important clues about how affective and cognitive processes function in those tasks. ■

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REFERENCES

1. J. von Neumann and O. Morgenstern, *Theory of Games and Economic Behavior*. Princeton, NJ: Princeton Univ. Press, 1953.
2. C. Dwork and A. Roth, "The algorithmic foundations of differential privacy," *Found. Trends Theoretical Comput. Sci.*, vol. 9, no. 3–4, pp. 211–407, 2014.
3. A. Ghosh, T. Roughgarden, and M. Sundararajan, "Universally utility-maximizing privacy mechanisms," *SIAM J. Comput.*, vol. 41, no. 6, pp. 1673–1693, 2012.
4. J. Y. Tsai, S. Egelman, L. Cranor, and A. Acquisti, "The effect of online privacy information on purchasing

behavior: An experimental study," *Inform. Syst. Res.*, vol. 22, no. 2, pp. 254–268, 2011.
5. P. W. Glimcher and E. Fehr, *Neuroeconomics, Decision Making and the Brain*. Amsterdam, The Netherlands: Elsevier, 2014.
6. S. A. Huettel, A. W. Song, and G. McCarthy, "Decisions under uncertainty: Probabilistic context influences activity of prefrontal and parietal cortices," *J. Neurosci.*, vol. 25, no. 13, pp. 3304–3311, 2005.
7. M. B. Miller, M. Valsangkar-Smyth, S. Newman, and H. Dumont, "Brain activations associated with probability matching," *Neuropsychologia*, vol. 43, no. 11, pp. 1598–1608, 2005.
8. D. Kahneman, *Thinking Fast and Thinking Slow*. New York: Farrar Straus, 2011.
9. A. Acquisti, "Privacy in electronic commerce and the economics of immediate gratification," in *Proc. ACM Conf. Electronic Commerce*, 2004, pp. 21–29.
10. S. Dhami, *Foundations of Behavioral Economic Analysis*. London: Oxford Univ. Press, 2016.
11. D. Kahneman and A. Tversky, "Prospect theory: An analysis of decision under risk," *Econometrica*, vol. 47, no. 2, pp. 263–292, 1979.
12. Y. Rottenstreich and C. K. Hsee, "Money, kisses, and electric shocks: On the affective psychology of risk," *Psychological Sci.*, vol. 12, no. 3, pp. 185–190, 2001.
13. S. Russell and P. Norving, *Artificial Intelligence: A Modern Approach*. Englewood Cliffs, NJ: Prentice Hall, 2010.
14. C. R. Fox and R. A. Poldrack, "Prospect theory and the brain," in *Handbook of Neuroeconomics*, P. Glimcher, C. Camerer, E. Fehr, and R. A. Poldrack, Eds. San Diego, CA: Academic, 2008, pp. 533–567.
15. F. Farahmand, "Decision and experienced utility: Computational applications in privacy decision making," *IEEE Security Privacy*, vol. 15, no. 6, pp. 68–72, 2017.

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