Psychological Evaluation of Human Choice Behavior in Socio-Technical Systems: A Rational Process Model Approach

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In the age of digital services and everyday smartphone usage, the issue of online privacy has gathered more and more interest for researchers, service providers and consumers. Assuming one's digital information is private is equivalent to trusting service providers to handle one's data in a certain way or ensuring protective measures against loss of privacy. When a consumer registers for an online service or installs a smartphone app, I assume an internal psychological process to relate the benefits of their decision to the risks associated with it. However, this process is considered to be subject of uncertainty. Therefore, decisions in a socio-technical environment can be viewed as decisions governed by a probabilistic amount of trust in an outcome, or, in other words, the amount of belief one holds that a hypothesis about future events will turn out to be true.

Previous research on human online behavior paints a fairly bleak picture of how we handle said uncertainty. It often adopts the paradigm of the Homo Heuristicus [1], relying on computational shortcuts rather than normatively rational inference. In a scenario as complex as online privacy, it also points out how unlikely it is for users to have a complete understanding of the capabilities and motives of involved parties [2].

However, psychological research on broader decision making processes includes evidence that humans are in fact able to combine information in a rational sense [3]. The Sampling Hypothesis [4] may provide the grounds for unifying research on heuristic or otherwise boundedly rational decision making on one hand with a rational account on the other. It does so by approximating Bayesian inference, sampling from probability distributions over possible hypotheses or parameter values instead of using these full distributions and creating implausibly complex computations. Its application shows that specific effects like the availability heuristic can actually be considered by-products of its sampling process [5]. Vul [4] provides evidence that in many situations, sampling only a very limited number of times provides a computationally similar result to using full yet analytically intractable probability distributions. Specifically, he links the benefits of sampling to the consumption of energy and time while arriving at a decision: why make one time- and energy-consuming decision perfectly maximizing my chance of success, when I can make many "good enough" decisions that approximate optimal results in the long run? This globally optimal solution however can produce seemingly irrational local behavior. Models that utilize such approximate Bayesian inference are termed rational process models [6].

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It appears as though human subjects, while certainly limited in their cognitive resources and computational capabilities as laid out by the bounded rationality paradigm, may make use of this process: they operate by maximizing success chances and making rational choices, but on a global rather than local level. My work utilizes this type of model to investigate how humans make decisions online, and more importantly how to sensitize them to make more adequate decisions to protect their private information. A preliminary study [7] indicates that answers to these questions are not as simple as pointing to a specific heuristic approach or a systematic gap between privacy-related attitudes and behavior. When asked whether they wanted to install a travel-related smartphone app involving beneficial and non-beneficial features, subjects showed behavioral patterns that were predicted by a rational process model. Preference trade-offs for the app's features form the basis of the model prediction as a posterior distribution. Then, sampling from said individual posterior provides the model with an approximate probability of choosing to install the app. The model stochastically chooses the option with higher utility according to its probability. It therefore allows for a seemingly irrational decision on the local level when choosing the option with lower utility instead. The rate with which subjects chose their higher utility option or deviated from it was predicted by the model, with a deviation of approximately 5% between its prediction and the empirical data. This deviation is not significantly different from zero, as indicated by a Bayesian estimation of the difference parameter between the two.

The model seems to capture the process with which subjects combine preferences about features as well as their trade-off between utility maximization and cognitive resource management. It is based on subjective utility distributions, thus avoiding the assumption of complete situational knowledge proposed in previous research [2] to arrive at a rational decision. These subjective utility distributions in turn can be learned solely based on past experience [8]. It is worth noting that heuristic or probability-weighted alternatives of the model, following a cumulative prospect theory (CPT) approach, could possibly have resulted in a decent statistical fit as well. CPT's parameter estimation [9] would likely capture stochastic variations descriptively if it was retrospectively fitted for a specific individual and trial. It would not, however, explain the nature of the variation or the necessity of the sampling process on theoretical grounds. Meanwhile, the rational process model approach outlined here unites the idea of Bayesian computational rationality in human cognition with limitations on the algorithmic level [10]. Additionally, it allows for an explanation of other phenomena observed in decision making research, like probability matching.

Based on the preliminary study, I plan to first adapt the model to other interactions with socio-technical systems. Secondly, I will explore specific mechanisms of the model to apply them to privacy interventions. For example, increasing the number of samples drawn in the model increases the chance of choosing an option with higher utility, instead of sometimes choosing a lower utility option. This may be achieved by asking subjects to state their choice repeatedly. Assuming a privacy-protecting decision (not installing an app that requires permissions to access private data) is a subject's higher utility option, an intervention increasing their internal sample count should result in a higher probability of choosing that option. However, there is a chance that they favor a privacy-disclosing option. In that case, an intervention designed to increase sampling counts might reinforce the tendency to pick the disclosing option, resulting in the opposite of the intended purpose. Future work will draw inspiration from how the mechanisms of sampling in decision making work to design privacy-protecting interventions tailored to individual preferences and thereby making use of the human tendency to operate on a globally rational level of information integration. Building on these rational process mechanisms, I aim to assess and direct user trust in the interaction with socio-technical systems as well as explain stochastic deviance from their expected behavior.

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