



# Toward a model of risky decisions: Synergistic effect of affect intensity and affective processing on risk-seeking as a function of decision domain<sup>☆</sup>

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## ABSTRACT

Four studies investigated the causal link of affect intensity with risky decisions, and showed a striking contrast of life-saving and valuables-saving domains. When social distance is small people are more risk-seeking in the life-saving domain but less risk-seeking in the valuables-saving domain (Study 1), and the results remain robust under different framings (Study 2). Relatedly, people rely more on affective processing when social distance is small in the life-saving domain, but not in the valuables-saving domain (Study 3). Furthermore, in the life-saving domain social distance exerts an effect on risk preference under affective processing but not under deliberate processing, whereas, in the valuables-saving domain, social distance influences risk preference under deliberate processing but not under affective processing (Study 4). A unified, causal model of risky decisions is proposed to account for these findings and the fundamental differences among decision domains in light of their relationships with the affective processing. The model has a potential to generalize into other decision domains.

## 1. Introduction

Emotions often accompany risky decisions, but the causal mechanisms can vary across situations. The current study seeks to pinpoint one of the causal links connecting emotion with risk preference in decisions, and examines how domains of decision moderate this connection.

## 2. Mode of processing and insensitivity to value variation

The classic dual mode of processing describes information processing with one end anchored at the intuitive and emotional *affective processing*, and the other end at the analytic and rational *deliberate processing* (Evans, 2008; Glöckner & Witteman, 2010; Mukherjee, 2010). Inasmuch as most decisions fall along the continuum of these two modes, the *affective psychology of value* argues for a discontinuity of cognitive patterns when decision-making approaches the pole of affective processing (Hsee & Rottenstreich, 2004). When people rely on feeling, they tend to make qualitative value judgment and are insensitive to value variation of the target. By contrast, people influenced primarily by deliberate processing are more sensitive to the scope of value variation.

The insensitivity to value variation is manifested in the shape of a value function, as depicted as the two labeled gray curves in Fig. 1. When individuals rely on deliberate processing, a linear function describes the relationship of an outcome (e.g., number of casualties) and the value given to it (e.g., rating how good the outcome is). When individuals rely on affective processing, one would first observe a maximal amount of value assigned to the best outcome (e.g., no person died), followed by a sharp drop in value at the next level (e.g., one person died), and a rapid decay until insensitivity to the value variation of the remaining outcomes. A step function or its continuous approximation (e.g., exponential curve in figure) theoretically describes the value variation under affective processing (Hsee & Rottenstreich, 2004).

## 3. An incomplete model of risky decisions: social distance and domain effect

According to dual-process theory in the realm of risk research, there are two fundamental ways to comprehend risk, risk-as-feelings and risk-as-analysis (Slovic, Finucane, Peters, & MacGregor, 2004), referring to affective processing and deliberate processing in risky decisions re-

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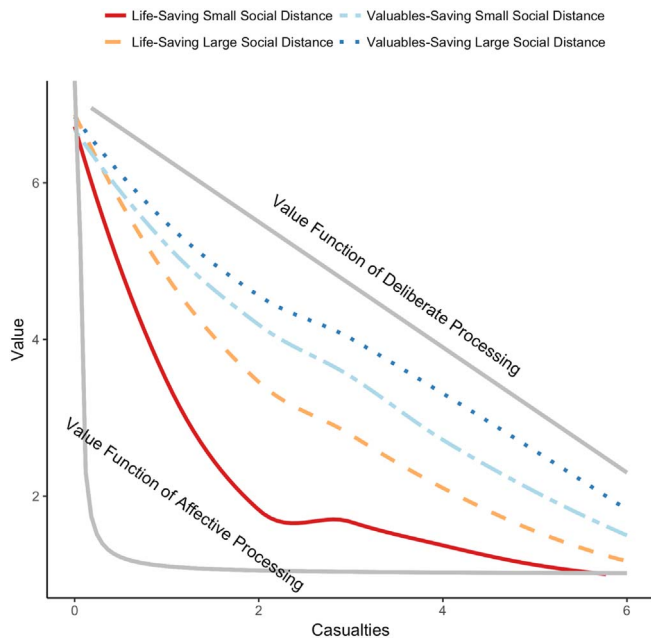


Fig. 1. Value functions describing value variations to outcome under affective and deliberate processing. The gray lines with labels (lower exponential and upper linear) describe the theoretical value functions for two modes of processing. The curves in between are loess fit lines based on data in Study 3 across four conditions with legends on top. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

spectively. Decisions driven by affective processing can often be risk-seeking. Since the second-best outcome is valued as undesirable as the worst outcome, individuals would be led to aim exclusively for the best outcome, which is the *only* desirable outcome. Such decisions involve greater risks. By contrast, decisions under deliberate processing would avert risks based on valuation adjustment.

Empirical research has mainly used two methods to operationalize affective processing. One method primes research subjects to rely on feeling in their decisions. The other method ramps up affect intensity in the experimental stimuli. Social distance is kind of psychological distance with the reference point to be the self, and describes the relationship closeness with others (Trope & Liberman, 2010), e.g., closest family members or friends are persons involving smaller social distance with the self, and strangers are those with larger social distance. A recent study shows that, in making life-saving decisions, small social distance between the subjects and the victims (corresponding to greater affect intensity) leads to higher risk preference, and the effect is stronger when subjects are instructed to use their “gut feelings” to make the decision (Zhang, Chen, Luan, & Li, 2016). These findings, combined with the theoretical proposition of affective psychology of value, have laid the foundation for a model of risky decisions. This model proposes that a synergy of affective processing and affect intensity can effectively trigger risk-seeking decisions.

However, these results are limited to a unique decision domain (i.e., life-saving), and thus the model is incomplete without including its boundaries. Research has shown that quantity insensitivity is often observed in decision domains where there is strong moral motivation to protect certain core values from being compromised (Baron & Greene, 1996; Baron & Spranca, 1997). It happens that the life-saving domain must favor affective processing, because value of human lives is highly moralized and the stakes of saving lives are so high that cost-benefit calculations are defied. However, we argue that most other decision domains (e.g., financial domain) would prioritize deliberate processing over affective processing to minimize the cost of risky decisions. In these domains, affective processing would not assume a dominant role, and the affective psychology of value would simply not apply.

#### 4. Current study and data analysis

The current study seeks to complete the model by drawing the boundary of the model with evidence from a different domain. We chose the valuables-saving situation to contrast with the life-saving situation, given that decisions in both situations are made to rescue a target but they differ in that valuables have price whereas lives are priceless.

Consistent with the previous study (Zhang et al., 2016), we kept social distance as manipulation of affect intensity, and feeling prime as manipulation of affective processing. In four studies, we would reproduce the findings in the life-saving situation, and show contrasting results in the valuables-saving situation. We would demonstrate that, in the valuables-saving domain, small social distance should not increase risk preference (Study 1 and Study 2); small social distance should not make people rely on affective processing (Study 3); and feeling priming should not catalyze risky decisions (Study 4).<sup>2</sup>

For all analyses reported in this paper, we adopted both the Frequentist and Bayesian approaches to test our hypotheses. The Frequentist approach conducted factorial ANOVA and reported F-tests associated with p-values and effect sizes. Sample sizes were informed with a priori power analysis. To obtain a power of 0.99 with alpha level of 0.05 in a 2 by 2 factorial design, the total sample size needed to be at least 90 for medium effect size ( $\delta = 0.50$  or  $\eta^2 = 0.06$ ), and at least 30 for large effect size ( $\delta = 1.00$  or  $\eta^2 = 0.20$ ). Previous studies suggested large effect sizes for the effect of social distance (Zhang et al., 2016), and we sampled  $N \geq 30$  when testing for that main effect. We assumed medium effect size for the effect of domain and included sample size of  $N = 90$  or larger for that purpose.

While conventional ANOVA allows researchers to test the presence of main and interaction effects against the null hypothesis, the Bayesian approach can state evidence for the *absence* of an effect (i.e., the null hypothesis). This advantage of Bayesian approach was especially relevant for analysis of data in the current studies where several hypotheses favored a null effect. In practice, psychologists often use Bayes factor to quantify the evidence for one model (e.g.,  $M_0$ ) compared to an alternative model (e.g.,  $M_1$ ). Bayes factor is defined as the ratio of the likelihood probability of two competing models. For instance, the Bayes factor of  $B_{10} = 10$  (comparing  $M_1$  to  $M_0$ ) means that the evidence favors  $M_1$  ten times over  $M_0$ ; likewise,  $B_{10} = 0.1$  means that the evidence favors  $M_0$  ten times as much as  $M_1$ . In the results section, we reported the  $B_{10}$  values indicating the degree to which the data favored or disfavored the alternative hypothesis over the null hypothesis. The MCMC chains were visually examined and estimating errors checked to make sure the model converged correctly.

Computation of Bayes factors used the ‘BayesFactor’ package in R. Non-informative Jeffreys’ priors were placed on the distribution of outcome variables (i.e., normally distributed with  $\mu$  and  $\sigma^2$ ). The prior for the variance of effect size was model as a scaled  $\chi^2$  distribution with one degree of freedom and the tuning parameter was set at 0.5 for an optimal coverage of prior effect sizes (Rouder, Morey, Verhagen, Swagman, & Wagenmakers, 2016). Interested readers can find rigorous mathematical account for computing Bayes factor in linear models (Rouder, Morey, Speckman, & Province, 2012).

#### 5. Study 1

Study 1 examined the influence of social distance on risk preference in life-saving or valuables-saving decisions. The primary hypotheses stated a moderating effect of domain on social distance:

**H1.1.** In the life-saving domain, small social distance would lead to higher risk preference.

<sup>2</sup> The link to our open data is [https://osf.io/rsf86/?view\\_only=06347220b77940638f75e961edd10805](https://osf.io/rsf86/?view_only=06347220b77940638f75e961edd10805).

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