Emotions in Games: Toward a Unified Process-Level Account

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Abstract

Strategic decision-making is chiefly studied in behavioral economics using multi-agent games. Decades of empirical research has revealed that emotions play a crucial role in strategic decision-making, calling into question the "emotionless" *homo economicus*. In this work, we present a unified process-level account of a broad range of empirical findings on the effect of emotions in Prisoner's Dilemma and Ultimatum games—the two most studied games in behavioral sciences. Under the empirically well-supported assumption that emotions modulate loss aversion, we show that Nobandegani et al.'s (2018) *sample-based expected utility* model can account for the effect of emotions on: (i) cooperation rate in Prisoner's Dilemma, and (ii) the rejection rate of unfair offers in the Ultimatum game. We conclude by discussing the implications of our work for emotion research, and for developing a unified process-level account of the role of emotions in strategic decision-making.

Keywords: emotions; strategic decision-making; behavioral game theory; Prisoner's dilemma; Ultimatum game; cooperation; fairness; sample-based expected utility

1 Introduction

Nearly four decades of empirical research has investigated the role of emotions in decision-making (for reviews see, e.g., Phelps et al., 2014; Lerner et al., 2015), collectively revealing that the effect of emotions on decision-making is both substantial and systematic. However, despite this wealth of emotion research, a process-level understanding of how emotions affect decision-making has remained largely elusive.

Here, we focus on the role of emotions in strategic decision-making—a domain of decision-making chiefly studied in behavioral economics using multi-agent games (Camerer, 2003)—and present a unified process-level account of a broad range of experimental findings on the effect of emotions in Ultimatum Game (UG) and Prisoner's Dilemma (PD), the two most studied games in behavioral sciences.

To this end, our work combines a resource-rational process model of risky choice, *sample-based expected utility* (SbEU; Nobandegani et al., 2018), with an overarching assumption on the role of emotions in decision-making: emotions affect decision-making by modulating *loss-aversion*—the tendency to overweight losses as compared to gains (Kahneman & Tversky, 1979).

The assumption of loss-aversion has received a wealth of empirical support from both behavioral and neuroimaging studies. For example, links have been established between loss-aversion and the amygdala (De Martino et al., 2010), a brain region known to be implicated in processing emotional responses. Also, high interoception—the awareness of one's own internal sensations, which entails sensitivity to markers of emotion—was associated with higher loss aversion (Sokol-Hessner et al., 2015). More directly, the difference in skin conductance response (a common measure of emotional arousal; Kreibig, 2010) to losses vs gains were correlated with loss aversion (Sokol-Hessner et al., 2009). Relatedly, changes in loss aversion were observed when participants were asked to regulate their emotions by thinking like a trader (Sokol-Hessner et al., 2009), considering each of their monetary choices in the broader context of their overall choices, as if they were creating a portfolio.

Specifically, we show that SbEU together with the broad assumption that negative emotions elevate loss-aversion while positive emotions lower loss-aversion can explain the effect of a wide range of emotions on the rejection rate of unfair offers in UG and cooperation rate in PD.

Our paper is organized as follows. We first explain the computational underpinnings of SbEU. We then review a range of empirically well-replicated findings in UG and PD and present a unified, process-level account of those findings. We conclude by discussing the implications of our work for emotion research, and for developing a unified process-level account of the role of emotions in strategic decision-making.

2 Sample-based Expected Utility Model

SbEU is a resource-rational process model of risky choice that posits that an agent rationally adapts their strategy depending on the amount of time available for decision-making (Nobandegani et al., 2018). Concretely, SbEU assumes that an agent estimates expected utility

$$\mathbb{E}[u(o)] = \int p(o)u(o)do, \tag{1}$$

using self-normalized importance sampling (Hammersley & Handscomb, 1964), with its importance distribution q^* aiming to optimally minimize mean-squared error (MSE):

$$\hat{E} = \frac{1}{\sum_{j=1}^{s} w_j} \sum_{i=1}^{s} w_i u(o_i), \quad \forall i:\ o_i \sim q^*,\ w_i = \frac{p(o_i)}{q^*(o_i)}, \tag{2}$$

$$q^*(o) \propto p(o)|u(o)|\sqrt{\frac{1+|u(o)|\sqrt{s}}{|u(o)|\sqrt{s}}}. \tag{3}$$

MSE is a standard measure of estimation quality, widely used in decision theory and mathematical statistics (Poor, 2013). In Eqs. (1-3), o denotes an outcome of a risky gamble, $p(o)$ the objective probability of outcome o, $u(o)$ the subjective utility of outcome o, $\hat{E}$ the importance-sampling estimate of expected utility given in Eq. (1), q^* the importance-sampling distribution, o_i an outcome randomly sampled from q^*, and s the number of samples drawn from q^*.

Recent work has provided mounting evidence suggesting that people often use very few samples in probabilistic judgments and decision-making (e.g., Vul et al., 2014; Nobandegani et al., 2019a, 2020; Nobandegani & Shultz, 2020a, 2020b, 2020c). Consistent with this finding, throughout this paper we assume that a player draws a single sample ($s = 1$) when making a decision.

Also, consistent with prospect theory (Kahneman & Tversky, 1979), in this paper we assume a standard S-shaped utility function $u(x)$ given by:

$$u(x) = \begin{cases} x^{0.85} & \text{if } x \geq 0 \\ -\lambda|x|^{0.95} & \text{if } x < 0 \end{cases} \tag{4}$$

where λ denotes the loss-aversion parameter.

Recently, Nobandegani and colleagues showed that SbEU provides a unified, resource-rational process model of several major experimental findings in UG and PD (Nobandegani et al., 2019a, 2020), suggesting that the broad framework of resource-rationality (Nobandegani, 2017; Lieder & Griffiths, 2020) may hold the key for developing a unified account of human strategic decision-making.

3 Effect of Emotions in Prisoner's Dilemma

The (one-shot) Prisoner's Dilemma (PD) is a canonical task for studying altruism and cooperation across a wide range of disciplines, e.g., biology (Turner & Chao, 1999), psychology (Rapoport & Chammah, 1965), neuroscience (Rilling et al., 2002), and behavioral economics (Camerer, 2003). In PD, two players must independently choose whether to cooperate or defect. Their payoffs are jointly determined by their choice and by their opponent's choice: if both cooperate, they each get payoff c (for mutual cooperation). If a player cooperates while the other player defects, the cooperator receives payoff v (the victim's payoff) and the defector receives payoff t (the temptation to defect). If both players defect, they each receive outcome d (for mutual defection). For PD, these parameters satisfy $t > c > d > v$. Although it is normatively irrational to cooperate in one-shot PD, substantial empirical evidence indicates that people often cooperate (e.g., Dawes & Thaler, 1988; Fehr & Gächter, 2000).

Recent experimental work has studied emotions in the context of standard PD or a variant thereof. In one variant, after playing PD and learning their opponent's choices, players were given the chance to punish or reward their opponent, at a cost to themselves. Players who inflicted costly punishment reported significantly higher levels of negative emotions including anger, while players who provided costly reward reported higher levels of positive emotion such as happiness (Duersch & Servátka, 2007).

Other studies, although not directly involving emotion measurement or manipulation, also suggest that emotion plays a role in decision-making in PD. Increased collaboration was observed after priming players with physical warmth, which is cognitively similar to pleasant intrapersonal warmth, as opposed to cold (Storey & Workman, 2013). Players cooperated more when their opponents were physically attractive, perhaps because these opponents triggered positive emotions (Mulford et al., 1998).

More directly, after an unrelated task which induced feelings of sympathy (or respectively anger) directed towards their opponent, participants were more (or respectively less) likely to cooperate (Eimontaite et al., 2019). Also, opponent's facial expressions associated with positive emotion predicted cooperation while those associated with negative emotion predicted defection (Reed et al., 2012).

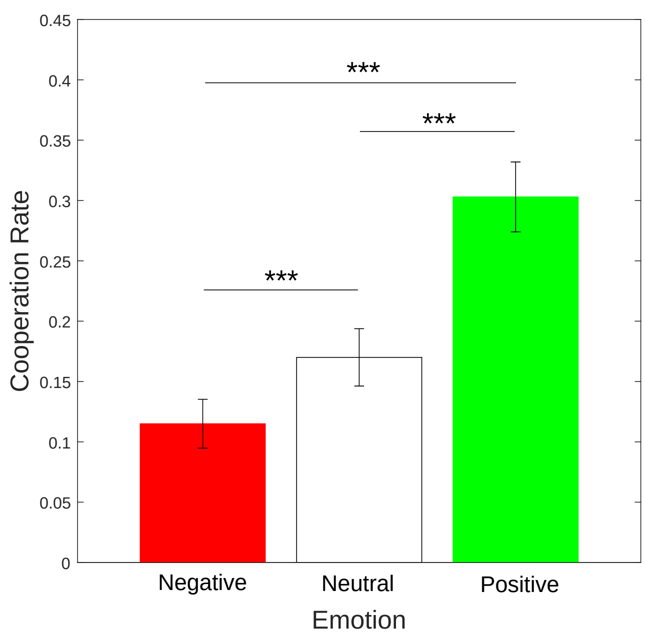

Figure 1: **Simulated effect of induced emotions on cooperation rate in PD.** The SbEU model predicts that induced positive emotions increase cooperation while, conversely, induced negative emotions decrease cooperation in PD. Error bars indicate binomial 95% CI. $^{***}p < .001$

Based on these experimental findings, the overwhelming impression is that induced positive emotions tend to increase cooperation while, conversely, induced negative emotions tend to decrease cooperation in PD. As Fig. 1 shows, SbEU together with the assumption that $\lambda_{\text{negative emotion}} > \lambda_{\text{neutral}} > \lambda_{\text{positive emotion}}$ provides a resource-rational process model of this result. This assumption is consistent with the empirically well-established finding that emotions affect decision-making by modulating loss-aversion (i.e., the λ parameter in Eq. 4); see Introduction for empirical evidence.

In our simulations (Fig. 1), we use a representative example of a PD game from Shafir and Tversky (1992), with payoffs $t = 85, c = 75, d = 30, v = 25$. Importantly, the trend of our simulation results is robust across a wide range of PD parameterizations. We use $\lambda_{\text{negative emotion}} = 3$, $\lambda_{\text{neutral}} = 2$, $\lambda_{\text{positive emotion}} = 1$; the trend of our simulation results is preserved as long as the ordering suggested by the assumption $\lambda_{\text{negative emotion}} > \lambda_{\text{neutral}} > \lambda_{\text{positive emotion}}$ is respected. Note that having to satisfy an ordering is a considerably weaker assumption, compared to having to precisely fine-tune parameters. We simulate 1000 participants.

4 Effect of Emotions in Ultimatum Game

The Ultimatum Game (UG; Güth et al., 1982) is a canonical task for studying fairness, and is extensively studied in brain and behavioral sciences (see Camerer, 2003). UG has a simple design. Two players, Proposer and Responder, have to agree on how to split a sum of money. Proposer makes an offer. If Responder accepts, the deal goes ahead; if Responder rejects, neither player gets anything. In both cases, the game is over. Normative standards of game theory predict that Responder will accept any nonzero offer, with the rationale being that any positive amount, even if minuscule, is better that nothing at all (Camerer & Thaler, 1995). Nevertheless, in sharp contrast to the predictions of these normative standards, a wealth of empirical evidence reveals that Responders predominantly reject offers below 30% (e.g., Güth et al., 1982; Thaler, 1988; Camerer & Fehr, 2006).

Another substantial body of experimental work has studied the link between UG Responder behavior and various markers of emotions that arise in response to unfair offers (i.e., *integral emotions*; see Lerner et al., 2015). For example, rejections of unfair offers were associated with measures of emotional arousal such as heart rate (Osumi & Ohira, 2009), skin conductance activity (van't Wout et al., 2006), and higher activity in brain areas related to emotion like the amygdala and the anterior insula (Gospic et al., 2011; Sanfey et al., 2003). In particular, a pharmacological intervention decreased both rejection rates and amygdala response to unfair offers, without affecting perceived unfairness (Gospic et al., 2011). Rejections were also correlated with the intensity of reported negative emotions (Bosman et al., 2001), more so than to perceived unfairness (Pillutla & Murnighan, 1996). There were also fewer rejections when Responders could express their feelings of anger to the Proposer (Xiao & Houser, 2005).

More surprisingly, there is mounting evidence that emotions that are unrelated to the task, aka *incidental emotions*, impact Responder's accept/reject decision in the UG, particularly for offers of less than 40% of the total (Riepl et al., 2016; Moretti & di Pellegrino, 2010). Experimentally, incidental emotions are often induced by a movie clip or recall task. When compared to a neutral emotion, incidental anger led to lower acceptance rates (Liu et al., 2016; Vargas et al., 2019), as did incidental sadness (Harlé et al., 2012; Harlé & Sanfey, 2007; Liu et al., 2016) and incidental disgust (Harlé & Sanfey, 2010; Liu et al., 2016; Moretti & di Pellegrino, 2010). Incidental happiness led to higher acceptance rates when compared to a neutral incidental emotion (Riepl et al., 2016), to incidental anger (Andrade & Ariely, 2009; Vargas et al., 2019) and to incidental sadness (Forgas & Tan, 2013).

Next, we focus on a range of empirically well-replicated findings on the effect of incidental emotions on UG Responder's acceptance rate (AR), and provide a unified process-level account of those findings. See Fig. 2 for corresponding SbEU simulation results.

Disgust vs Neutral. Four studies found that incidental disgust leads to lower AR, compared to neutral emotion (Bonini et al., 2011; Harlé & Sanfey, 2010; Liu et al., 2016; Moretti & di Pellegrino, 2010).

Anger vs Neutral. Two studies found that incidental anger leads to lower AR, compared to neutral emotion (Liu et al., 2016; Vargas et al., 2019).

Happiness vs Sadness. Forgas and Tan (2013) found that incidental happiness yields higher AR than incidental sadness.

Sadness vs Disgust. Moretti and di Pellegrino (2010) found that incidental sadness yields higher AR than incidental disgust.

Happiness vs Neutral. Riepl et al. (2016) found that incidental happiness leads to higher AR, compared to neutral emotion.

Happiness vs Anger. Two studies found higher AR for incidental happiness than for incidental anger (Andrade & Ariely, 2009; Vargas et al., 2019).

Sadness vs Neutral. Three studies found that incidental sadness lowers AR, compared to neutral emotion (Harlé et al., 2012; Harlé & Sanfey, 2007; Liu et al., 2016).

Overall, these experimental findings involve five emotions: three negative emotions (disgust, anger, and sadness), one neutral emotional state (neutral), and a single positive emotion (happiness). As in Sec. 3, to simulate these experimental findings, we assume that $\lambda_{\text{negative emotion}} > \lambda_{\text{neutral}} > \lambda_{\text{positive emotion}}$. This assumption is consistent with the empirically well-established finding that emotions affect decision-making by modulating loss-aversion (i.e., the λ parameter in Eq. 4); see Introduction for empirical evidence.

However, to account for the full range of these empirical results, we need to further specify how the λ parameter varies within the category of negative emotions (i.e., emotions with negative valence). Hence, we tentatively assume $\lambda_{\text{disgust}} > \lambda_{\text{anger}} > \lambda_{\text{sadness}} > \lambda_{\text{neutral}} > \lambda_{\text{happiness}}$. Importantly, the trend of our simulation results is preserved as long as emotion-specific λ parameters respect the ordering suggested by this assumption. Note that having to satisfy an ordering is a considerably weaker assumption, compared to having to precisely fine-tune parameters. For simulation results reported in

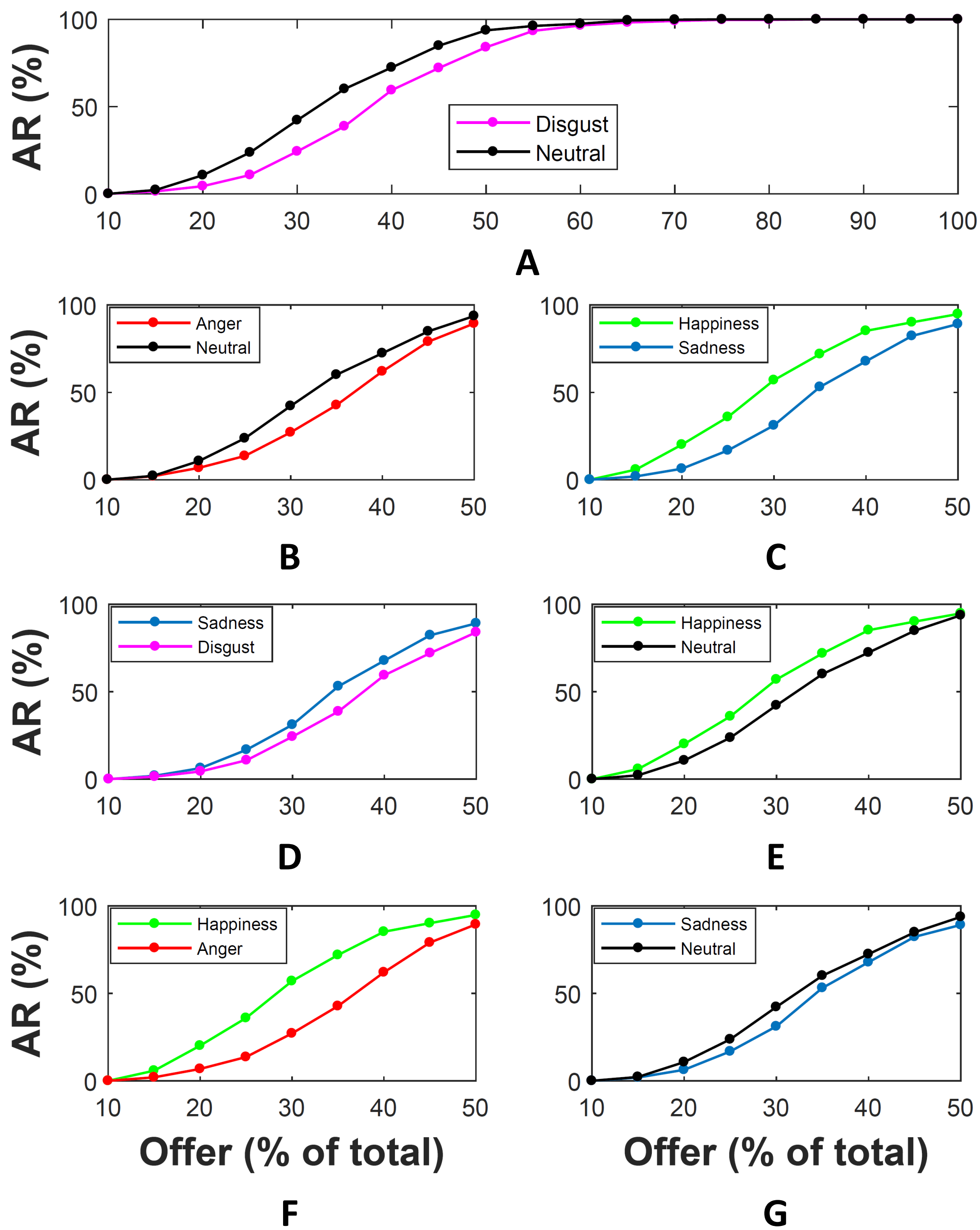

Figure 2: **Simulating the effect of incidental emotions on UG Responder's acceptance rate (AR).** In each subplot, the x-axis shows percent of offer made to Responder, and the y-axis shows AR. The SbEU model predicts that: **(A)** incidental disgust lowers AR compared to neutral emotion; **(B)** incidental anger lowers AR compared to neutral emotion; **(C)** incidental happiness increases AR compared to incidental sadness; **(D)** incidental sadness increases AR compared to incidental disgust; **(E)** incidental happiness increases AR compared to neutral emotion; **(F)** incidental happiness increases AR compared to incidental anger; **(G)** incidental sadness lowers AR compared to neutral emotion. We simulated 1000 participants.

Fig. 2, we use $\lambda_{\text{disgust}} = 5, \lambda_{\text{anger}} = 4, \lambda_{\text{sadness}} = 3, \lambda_{\text{neutral}} = 2, \lambda_{\text{happiness}} = 1$. We simulate 1000 participants.

As shown in Fig. 2, the SbEU model predicts that incidental emotions have virtually no effect on acceptance rate of offers greater than 50% of the total (with such offers being almost invariably accepted, as in the original UG), a prediction well-supported by empirical evidence (Moretti & di Pellegrino, 2010; Riepl et al., 2016).

5 General Discussion

Decades of experimental work has shown that emotions influence decision-making, both systematically and substantially (see Lerner et al., 2015). Nevertheless, despite a wealth of emotion research, a process-level understanding of how emotions affect decision-making has remained largely unknown.

In this work, we present a unified process-level account of a broad range of empirical findings on the effect of emotions in Prisoner's Dilemma (PD) and Ultimatum Game (UG)—the two most studied games in behavioral sciences. Our work shows that *sample-based expected utility* (SbEU; Nobandegani et al., 2018), a resource-rational process model of risky choice, together with the assumption that negative emotions elevate loss-aversion while positive emotions lower loss-aversion (i.e., $\lambda_{\text{negative emotion}} > \lambda_{\text{neutral}} > \lambda_{\text{positive emotion}}$) can explain the effect of a wide range of emotions on the rejection rate of unfair offers in UG and cooperation rate in PD. Importantly, this assumption is consistent with the empirically well-supported hypothesis that emotions affect decision-making by modulating loss-aversion; see Introduction for empirical evidence.

Interestingly, the hypothesis that emotions modulate loss-aversion suggests that emotions could be localized along the λ-axis, thus opening up a new research program aiming to quantitatively uncover the signature of every emotion on the λ-axis. Our work contributes to this intriguing research program by demonstrating the explanatory power of the assumption $\lambda_{\text{negative emotion}} > \lambda_{\text{neutral}} > \lambda_{\text{positive emotion}}$ in unifying a broad range of emotion research findings in strategic decision-making. It is worth noting that, according to our work, every emotion could occupy an interval on the λ-axis, with each point in that interval corresponding to some arousal level, and these intervals need not be non-overlapping (e.g., weakly-induced disgust and strongly-induced anger might both result in the same λ value). Alternatively, every emotion might be inducing a probability distribution on a region of the λ-axis, and, again, these regions need not be non-overlapping. Future research should delineate the range of λ values associated with various emotions.

Besides loss-aversion, emotions would likely affect choice behavior by modulating other key components of decision-making, e.g., number of mental simulations performed by an agent before deciding (aka samples, operationalized by parameter s; see Sec. 2). Future work should rigorously investigate how various emotions affect the number of mental simulations people perform when deciding. This investigation would be critical if a process-level understanding of emotions is to be developed within the broad framework of resource-rationality (Nobandegani, 2017; Lieder & Griffiths, 2020).

Recent work has shown that SbEU explains a broad range of empirical findings in risky, value-based, and strategic decision-making (see Nobandegani et al., 2020; Nobandegani, Shultz, & Dubé, 2021), successfully bridging between these three domains of decision-making. Together with the current study, these results suggest that the framework of resource-rationality may hold the key for developing a unified process-level account of decision-making. We see our work as a step in this direction.

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References

Andrade, E. B., & Ariely, D. (2009). The enduring impact of transient emotions on decision making. *Organizational Behavior and Human Decision Processes*, *109*(1), 1–8.

Bonini, N., Hadjichristidis, C., Mazzocco, K., Demattè, M. L., Zampini, M., Sbarbati, A., & Magon, S. (2011). Pecunia olet: the role of incidental disgust in the ultimatum game. *Emotion*, *11*(4), 965.

Bosman, R., Sonnemans, J., Zeelenberg, M., et al. (2001). Emotions, rejections, and cooling off in the ultimatum game. *Working paper*.

Camerer, C. F. (2003). *Behavioral Game Theory: Experiments in Strategic Interaction*. Princeton University Press.

Camerer, C. F., & Fehr, E. (2006). When does "economic man" dominate social behavior? *Science*, *311*, 47–52.

Camerer, C. F., & Thaler, R. H. (1995). Anomalies: Ultimatums, dictators and manners. *Journal of Economic Perspectives*, *9*(2), 209–219.

Dawes, R. M., & Thaler, R. H. (1988). Anomalies: cooperation. *Journal of Economic Perspectives*, *2*(3), 187–197.

De Martino, B., Camerer, C. F., & Adolphs, R. (2010). Amygdala damage eliminates monetary loss aversion. *PNAS*, *107*(8), 3788–3792.

Duersch, P., & Servátka, M. (2007). Risky punishment and reward in the prisoner's dilemma. *working paper*.

Eimontaite, I., Schindler, I., De Marco, M., Duzzi, D., Venneri, A., & Goel, V. (2019). Left amygdala and putamen activation modulate emotion driven decisions in the iterated prisoners dilemma game. *Front in Neuro*, *13*, 741.

Fehr, E., & Gachter, S. (2000). Cooperation and punishment in public goods experiments. *Econ Rev*, *90*(4), 980–994.

Forgas, J. P., & Tan, H. B. (2013). To give or to keep? affective influences on selfishness and fairness in computer-mediated interactions in the dictator game and the ultimatum game. *Computers in Human Behavior*, *29*(1), 64–74.

Gospic, K., Mohlin, E., Fransson, P., Petrovic, P., Johannesson, M., & Ingvar, M. (2011). Limbic justiceamygdala involvement in immediate rejection in the ultimatum game. *PLoS Biology*, *9*(5), e1001054.

Güth, W., Schmittberger, R., & Schwarze, B. (1982). An experimental analysis of ultimatum bargaining. *Journal of Economic Behavior & Organization*, *3*(4), 367–388.

Hammersley, J., & Handscomb, D. (1964). *Monte Carlo Methods.* London: Methuen & Co Ltd.

Harlé, K. M., Chang, L. J., van't Wout, M., & Sanfey, A. G. (2012). The neural mechanisms of affect infusion in social economic decision-making: a mediating role of the anterior insula. *Neuroimage*, *61*(1), 32–40.

Harlé, K. M., & Sanfey, A. G. (2007). Incidental sadness biases social economic decisions in the ultimatum game. *Emotion*, *7*(4), 876.

Harlé, K. M., & Sanfey, A. G. (2010). Effects of approach and withdrawal motivation on interactive economic decisions. *Cognition and Emotion*, *24*(8), 1456–1465.

Kahneman, . T. A., D. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–291.

Kreibig, S. D. (2010). Autonomic nervous system activity in emotion: A review. *Biol Psych*, *84*(3), 394–421.

Lerner, J. S., Li, Y., Valdesolo, P., & Kassam, K. S. (2015). Emotion and decision making. *Annual Rev Psych*, *66*.

Lieder, F., & Griffiths, T. L. (2020). Resource-rational analysis: Understanding human cognition as the optimal use of limited computational resources. *BBS*, *43*.

Liu, C., Chai, J. W., & Yu, R. (2016). Negative incidental emotions augment fairness sensitivity. *Sci Rep*, *6*, 24892.

Moretti, L., & Di Pellegrino, G. (2010). Disgust selectively modulates reciprocal fairness in economic interactions. *Emotion*, *10*(2), 169.

Mulford, M., Orbell, J., Shatto, C., & Stockard, J. (1998). Physical attractiveness, opportunity, and success in everyday exchange. *American J Soci*, *103*(6), 1565–1592.

Nobandegani, A. S. (2017). *The Minimalist Mind: On Mininality in Learning, Reasoning, Action, & Imagination*. McGill University, PhD Dissertation.

Nobandegani, A. S., da Silva Castanheira, K., Otto, A. R., & Shultz, T. R. (2018). Over-representation of extreme events in decision-making: A rational metacognitive account. In: *Proceedings of the* 40th *Annual Conference of the Cognitive Science Society* (pp. 2391-2396).

Nobandegani, A. S., da Silva Castanheira, K., Shultz, T. R., & Otto, A. R. (2019a). A resource-rational mechanistic approach to one-shot non-cooperative games: The case of Prisoner's Dilemma. In: *Proceedings of the* 41st *Annual Conference of the Cognitive Science Society.*.

Nobandegani, A. S., Destais, C., & Shultz, T. R. (2020). A resource-rational process model of fairness in the Ultimatum game. In *Proceedings of the* 42nd *Annual Conference of the Cognitive Science Society*.

Nobandegani, A. S., & Shultz, T. R. (2020a). A resource-rational mechanistic account of human coordination strategies. In *Proceedings of the* 42nd *Annual Conference of the Cognitive Science Society*.

Nobandegani, A. S., & Shultz, T. R. (2020b). A resource-rational, process-level account of the St. Petersburg paradox. *Topics in Cognitive Science*, *12*(1), 417–432.

Nobandegani, A. S., & Shultz, T. R. (2020c). The St. Petersburg paradox: A fresh algorithmic perspective. In *Proc. of the* 34th *Conference on Artificial Intelligence (AAAI)*.

Nobandegani, A. S., Shultz, T. R., & Dubé, L. (2021). A unified, resource-rational account of the Allais and Ellsberg paradoxes. In *Proceedings of the* 43rd *Annual Conference of the Cognitive Science Society*.

Osumi, T., & Ohira, H. (2009). Cardiac responses predict decisions: An investigation of the relation between orienting response and decisions in the ultimatum game. *International Journal of Psychophysiology*, *74*(1), 74–79.

Phelps, E. A., Lempert, K. M., & Sokol-Hessner, P. (2014). Emotion and decision making: multiple modulatory neural circuits. *Annual Rev Neuro*, *37*, 263–287.

Pillutla, M. M., & Murnighan, J. K. (1996). Unfairness, anger, and spite: Emotional rejections of ultimatum offers. *Org Beh and Human Decision Processes*, *68*(3), 208–224.

Poor, H. V. (2013). *An Introduction to Signal Detection and Estimation*. Springer Science & Business Media.

Rapoport, A., & Chammah, A. M. (1965). *Prisoner's dilemma: A study in conflict and cooperation* (Vol. 165). University of Michigan press.

Reed, L. I., Zeglen, K. N., & Schmidt, K. L. (2012). Facial expressions as honest signals of cooperative intent in a one-shot anonymous prisoner's dilemma game. *Evolution and Human Behavior*, *33*(3), 200–209.

Riepl, K., Mussel, P., Osinsky, R., & Hewig, J. (2016). Influences of state and trait affect on behavior, feedback-related negativity, and p3b in the ultimatum game. *PloS One*, *11*(1), e0146358.

Rilling, J. K., Gutman, D. A., Zeh, T. R., Pagnoni, G., Berns, G. S., & Kilts, C. D. (2002). A neural basis for social cooperation. *Neuron*, *35*(2), 395–405.

Sanfey, A. G., Rilling, J. K., Aronson, J. A., Nystrom, L. E., & Cohen, J. D. (2003). The neural basis of economic decision-making in the ultimatum game. *Science*, *300*(5626), 1755–1758.

Shafir, E., & Tversky, A. (1992). Thinking through uncertainty: Nonconsequential reasoning and choice. *Cognitive Psychology*, *24*(4), 449–474.

Sokol-Hessner, P., Hartley, C. A., Hamilton, J. R., & Phelps, E. A. (2015). Interoceptive ability predicts aversion to losses. *Cognition and Emotion*, *29*(4), 695–701.

Sokol-Hessner, P., Hsu, M., Curley, N. G., Delgado, M. R., Camerer, C. F., & Phelps, E. A. (2009). Thinking like a trader selectively reduces individuals' loss aversion. *PNAS*, *106*(13), 5035–5040.

Storey, S., & Workman, L. (2013). The effects of temperature priming on cooperation in the iterated prisoner's dilemma. *Evolutionary Psychology*, *11*(1), 52–67.

Thaler, R. H. (1988). Anomalies: The ultimatum game. *Journal of Economic Perspectives*, *2*(4), 195–206.

Turner, P. E., & Chao, L. (1999). Prisoner's dilemma in an rna virus. *Nature*, *398*(6726), 441–443.

Van't Wout, M., Kahn, R. S., Sanfey, A. G., & Aleman, A. (2006). Affective state and decision-making in the ultimatum game. *Exp Brain Research*, *169*(4), 564–568.

Vargas, M. E. S., Brown, A.-L., Durkee, C. M., & Sim, H. (2019). Blocking incidental frustration during bargaining. *Cognition and Emotion*, *33*(2), 146–156.

Vul, E., Goodman, N., Griffiths, T. L., & Tenenbaum, J. B. (2014). One and done? optimal decisions from very few samples. *Cognitive Science*, *38*(4), 599–637.

Xiao, E., & Houser, D. (2005). Emotion expression in human punishment behavior. *Proceedings of the National Academy of Sciences*, *102*(20), 7398–7401.