Contextually-Based Utility: An Appraisal-Based Approach at Modeling Framing and Decisions

Jonathan Ito and **Stacy Marsella**
Institute for Creative Technologies
University of Southern California
12015 Waterfront Drive
Playa Vista, CA 90094-2536 USA

Abstract

Creating accurate computational models of human decision making is a vital step towards the realization of socially intelligent systems capable of both predicting and simulating human behavior. In modeling human decision making, a key factor is the psychological phenomenon known as "framing", in which the preferences of a decision maker change in response to contextual changes in decision problems. Existing approaches treat framing as a one-dimensional contextual influence based on the perception of outcomes as either gains or losses. However, empirical studies have shown that framing effects are much more multifaceted than one-dimensional views of framing suggest. To address this limitation, we propose an integrative approach to modeling framing which combines the psychological principles of cognitive appraisal theories and decision-theoretic notions of utility and probability. We show that this approach allows for both the identification and computation of the salient contextual factors in a decision as well as modeling how they ultimately affect the decision process. Furthermore, we show that our multi-dimensional, appraisal-based approach can account for framing effects identified in the empirical literature which cannot be addressed by one-dimensional theories, thereby promising more accurate models of human behavior.

Introduction

Creating accurate computational models of human decision making is a vital step towards the realization of socially intelligent systems capable of both predicting and simulating human behavior. This is critical across a diverse range of applications such as those found in social simulation (Davidsson 2001), virtual-human based training (Rickel et al. 2002), interactive health intervention (Marsella, Johnson, and LaBore 2003; Bickmore, Gruber, and Picard 2005), and embodied conversational agents (Gratch and Marsella 2004). Additionally, accurate decision models are a necessary component in *prescriptive* decision systems, which assist people in making rational and goal-oriented decisions.

A key factor in modeling human decision making, and one that has garnered little attention in the AI community, is the phenomenon known as "framing", in which the preferences of an individual change in response to contextual changes in a decision scenario. In a seminal study involving what is referred to as the Asian Disease Scenario (ADS), Kahneman and Tversky (1979) demonstrated that changing the description of an outcome can lead to dramatic shifts in preference. The scenario, shown in Listing 1, consists of two distinct frames in which the same underlying outcomes are described, or framed, as either gains (survival frame) or losses (mortality frame). For instance, the outcome of Program A in the survival frame is equivalent to the outcome in Program C of the mortality frame; both describe a situation in which 200 people live while 400 die. In the original study, 72% of respondents in the survival frame preferred the risk-averse choice of Program A. However, when presented with the mortality frame, 78% preferred the risk-seeking choice of Program D.

Imagine that the U.S. is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimate of the consequences of the programs are as follows:
Survival Frame:

- Program A: 200 people will be saved.
- Program B: 1/3 probability that 600 people will be saved and 2/3 probability that none will be saved.

Mortality Frame:

- Program C: 400 people will die.
- Program D: 1/3 probability that nobody will die and 2/3 probability that 600 people will die.

Listing 1: Asian Disease Scenario

Subsequent studies involving domains as diverse as financial planning (Schoorman et al. 1994), taxes (Highhouse and Paese 1996) and Acquired Immune Deficiency Syndrome (Levin and Chapman 1990) have also demonstrated framing effects to varying degrees.

Existing approaches for modeling framing include Cumulative Prospect Theory (CPT) (Tversky and Kahneman 1992) and the Security-Potential/Aspiration Model (SP/A) (Lopes 1987). Both approaches model framing as a one-dimensional contextual influence predicated on the perception of outcomes as gains or losses. While both models account for the classic framing effect, i.e., risk aversion in gains and risk seeking in losses, numerous empirical studies within the framing literature have shown a great deal of variance and inconsistency in the classic framing effect which suggests that a one-dimensional view of framing is descriptively incomplete (Schneider 1992; Bohm and Lind 1992; Fagley and Miller 1987; Fagley and Kruger 1986).

In particular, one-dimensional approaches such as CPT and SP/A have difficulty accounting for the moderating effects on framing brought about by providing choice rationale and the resistance to framing evinced by expert decision makers.

In this work, we propose a framework for decision making under risk which is descriptively flexible enough to model a wide range of framing effects while remaining intuitive and easily operationalizable. Specifically, we show that by employing psychological principles of cognitive appraisal we can identify, extract, and compute the salient contextual aspects of a given decision scenario in a largely automated manner. This appraisal information can then be used to inform a weighted utility function resulting in a decision process which is descriptively more accurate than existing theories.

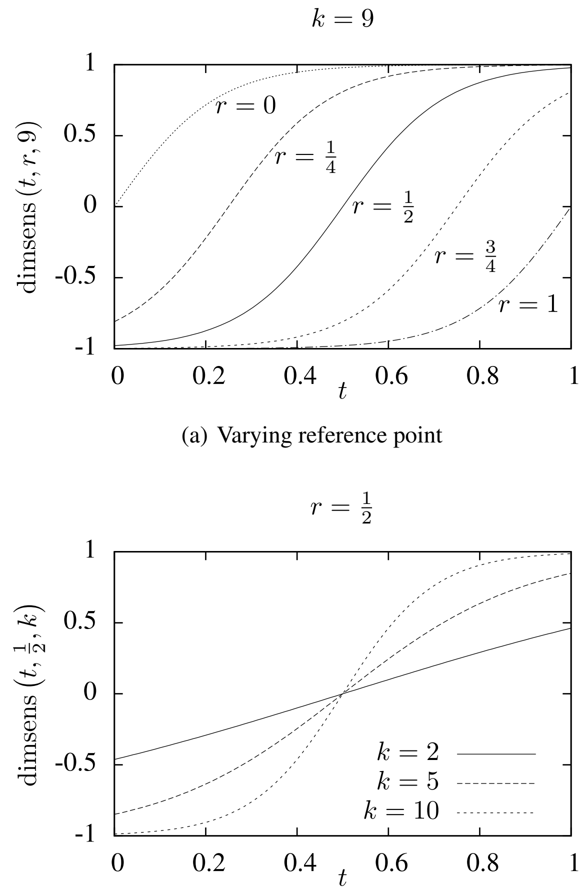
Approach

Our approach in creating a contextually-based, descriptive, decision framework consists of two primary components: the computational appraisal of decision outcomes and a decision evaluation function which incorporates the appraisal information.

Cognitive Appraisal of Outcomes

The process of cognitive appraisal, as defined in Appraisal Theory, is an evaluation of personal significance over several dimensions regarding an individual's relationship with herself, the environment, and others by which emotions are differentiated and elicited for a given stimulus (Arnold 1960; Lazarus 1991). It is precisely this assessment of personal significance, with respect to the environment of the decision maker, which provides us with a rich discretization of the key contextual factors, or situational variables, involved in a decision.

In this work, computational appraisal is defined as a function of diminishing sensitivity evaluated with respect to some reference point. This definition represents both the tendency of emotional habituation, in which continually increasing affect loses poignancy, and the notion that emotions and appraisals are elicited not by the outcomes themselves but by the *changes* which accompany them (Frijda 2007). This suggests an S-shaped function in which the reference point serves as the point of inflection. Therefore, a logistic function is employed to model diminishing sensitivity, which forms the computational basis of appraisal, shown in (1), in which the impact of t diminishes as it moves further from the reference point r. Additionally, the constant k, where $k \geq 1$, controls the degree of diminishing sensitivity. The result of this function is a real value between -1 and 1 such that positive values correspond to positive appraisals, e.g., appraisals of pleasantness, and negative values correspond to negative appraisals, e.g., appraisals of unpleasantness. Sample plots of the diminishing sensitivity function are shown in Figures 1(a) and 1(b) in which both the reference point and the sensitivity, k, are respectively varied.



(a) Varying reference point

(b) Varying sensitivity

Figure 1: Diminishing Sensitivity Function Plots

$$\mathrm{dimsens}\,(t, r, k) = \frac{2}{1.0 + \exp\left(-k\,(t - r)\right)} - 1 \quad (1)$$

In this work, we present three concrete appraisal functions defined over outcomes: pleasantness, goal congruence, and control. These three dimensions are chosen both because they are widely represented in the appraisal literature and can also be directly linked to notions of probability and value, both of which are highly pertinent in decision-theoretic domains.

It is important to note that our goal in this work is *not* to implement a full computational model of appraisal, as many promising implementations already exist (Gratch and Marsella 2004; Aylett, Dias, and Paiva 2006; Dias and Paiva 2005; Si, Marsella, and Pynadath 2010). Rather, we seek to leverage the principles underlying cognitive appraisal to model the effect of framing on decision processes. Moreover, while the three dimensions represented in our framework comprise only a subset of the appraisal dimensions found in the literature, they provide a foundation on which to build a decision function.

In what follows, a decision scenario is represented using a standard decision-theoretic representation. A scenario consists of n distinct alternatives, in which the ith alternative is labeled x_i. Each alternative results in one of n_i possible outcomes, in which the jth outcome is denoted as outcome $x_{i,j}$. The probability of obtaining outcome $x_{i,j}$, when alternative x_i is chosen, is given by the probability function $\mathrm{p}\left(x_{i,j}\right)$. Additionally, the associated value of outcome $x_{i,j}$ is $\mathrm{v}\left(x_{i,j}\right)$ and is generally encoded directly from the numerical description of an outcome, e.g., amount of money won, number of lives lost.

Pleasantness Pleasantness is the intrinsic attractiveness or unattractiveness of an outcome. Appraisals of pleasantness play a central role in many predominant structural theories of cognitive appraisal (Roseman 1984; Scherer 1982; Smith and Ellsworth 1985; Ortony, Clore, and Collins 1990). Pleasantness is an evaluation of value made with respect to the *status quo* (sq) as in (2).

$$\mathrm{pleas}\left(x_{i,j}\right) = \mathrm{dimsens}\left(\mathrm{v}\left(x_{i,j}\right), sq, \mathrm{k}\right) \tag{2}$$

The status quo serves as the reference point differentiating pleasant from unpleasant outcomes. In other words, outcomes more preferred than the status quo are appraised as pleasant, whereas less-preferred outcomes are perceived as unpleasant. The status quo itself is the state resulting in no change of current state for the decision-maker. In many decision scenarios, an explicit status quo is not provided. Oftentimes, the most natural location for it, and which is usually implied by convention, is the state associated with the 0-value, e.g., 0 lives lost, 0 dollars gained.

Goal Congruence Goal congruence is the degree to which an outcome fulfills the adopted goals of the decision maker which are heavily influenced by standards, expectations, and responsibilities. Goal congruence, like pleasantness, is well represented in the appraisal literature (Scherer 1982; Roseman 1984; Smith and Lazarus 1990). We represent goal congruence as an evaluation of value made with respect to the *aspiration outcome* (ao) as in (3).

$$\mathrm{gc}\left(x_{i,j}\right) = \mathrm{dimsens}\left(\mathrm{v}\left(x_{i,j}\right), ao, \mathrm{k}\right) \tag{3}$$

The aspiration outcome is the outcome which the decision maker aspires to and represents her adopted expectations, standards, morals, and obligations. Outcomes more preferred than the aspiration outcome are said to be *congruent* with the goals of the decision maker whereas less-preferred outcomes are *incongruent*. It can be argued that a rational location for the aspiration outcome is the maximum expected value of the scenario. However, as noted earlier, the imposition of external standards and expectations, even when self-imposed, may influence the aspiration outcome.

Control Control is a measure of the degree of agency and influence that a decision maker has in a scenario. It is conceptualized as both a form of agency (Roseman 1984; Smith and Ellsworth 1985) and as a critical component in coping potential (Smith and Lazarus 1990; Scherer 1982). Control is an evaluation of *decumulative* probability made with respect to some *expectation of control* (ec) as seen in (4). The decumulative aspect of control, shown in (5), is the total probability of achieving an outcome as good as $x_{i,j}$, in which outcomes are ordered from worst to best by value. This corresponds to the intuition that even a highly uncertain outcome, i.e., an outcome with a very low probability of occurrence, can be perceived as highly controllable if the other alternate outcomes are even more preferred. In other words, control is implemented not as a function of likelihood over the occurrence of a *singular* outcome but rather as a function of likelihood over the achievement of a certain value threshold.

$$\mathrm{ctrl}\left(x_{i,j}\right) = \mathrm{dimsens}\left(\mathrm{d}\left(x_{i,j}\right), ec, \mathrm{k}\right) \tag{4}$$

$$\mathrm{d}\left(x_{i,j}\right) = \sum_{k=j}^{n_i} \mathrm{p}\left(x_{i,k}\right) \tag{5}$$

The expectation of control establishes a reference point by which it is judged whether outcomes are controllable or uncontrollable. While the expectation of control is certainly influenced by situational variables such as the manner in which the uncertainty in a scenario is described, it is also subject to personal and individual factors such as locus of control (Rotter 1966). The concept of locus of control distinguishes between two sources of control: internal and external. Internals tend to believe that they control their own destiny and that outcomes are largely determined by their efforts which is suggestive of a lower expectation of control. That is, outcomes need only exceed a fairly low threshold of likelihood in order to be perceived as controllable. Externals, on the other hand, tend to attribute successes or failures to external forces such as nature, destiny, and other agents which is suggestive of a higher expectation of control.

Contextually-Based Utility (CBU) Decision Evaluation

The second component in our approach to modeling contextually-based decision making is the implementation of a decision function over the alternatives available in a decision.

The CBU function evaluates an alternative, x_i, and maps it to a real-value such that x_i is preferred at least as much as alternative x_j if and only if $\mathrm{CBU}\left(x_i\right) \geq \mathrm{CBU}\left(x_j\right)$. The CBU function takes the form of a standard decumulatively-weighted utility function, also commonly referred to as a rank-dependent utility model (Quiggin 1982); it is comprised of both a weighting component, w, and a utility function, u, as in (6) in which outcomes are ordered from worst to best. The decumulative component, $\mathrm{d}\left(x_{i,j}\right)$, is the total probability that an outcome *as good as* $x_{i,j}$ will be obtained and is defined identically to (5).

$$\mathrm{CBU}\left(x_i\right) = \sum_{j=1}^{n_i} \mathrm{w}\left(\mathrm{d}\left(x_{i,j}\right)\right)\left(\mathrm{u}\left(x_{i,j}\right) - \mathrm{u}\left(x_{i,j-1}\right)\right) \quad (6)$$

The decumulative form is employed to allow for the variable weighting of outcomes, such as either an optimistic over-weighting of desirable outcomes or a pessimistic over-weighting of undesirable outcomes, while preserving stochastic dominance. Stochastic dominance, stated simply, is a highly desirable decision-theoretic principle asserting that an alternative x_i should be preferred at least as much as alternative x_j if all outcomes of x_i are preferred at least as much as the outcomes of x_j.

In what follows, we show how the various dimensions of our previously defined appraisal process relate to the weighting and utility components of the CBU function. Specifically, we show that appraisals of control inform the weighting component while appraisals of pleasantness and goal congruence form a multi-attribute utility function.

Control as a Decision Weight The decision-weighting function, a function of probability and likelihood, represents the intensity and relative importance of a particular outcome. Note that both our implementation of control, shown in (4), and the weighting function $\mathrm{w}\left(x_{i,j}\right)$ are defined as functions of decumulative probability. Therefore, we use the previously defined appraisal of control to inform the weighting function.

The full control-based decumulative-weighting function, w, is given in (7) in which the weighting function is the appraisal of control normalized such that its range is between 0 and 1.

$$\mathrm{w}\left(x_{i,j}\right) = \frac{1}{2}\,\mathrm{ctrl}\left(x_{i,j}\right) + \frac{1}{2} \quad (7)$$

Pleasantness and Goal Congruence as a Multi-Attribute Utility Function The utility function, which maps an outcome to a real value, is representative of the "goodness" of an outcome and is independent of considerations of weight or probability. We therefore employ the appraisals of pleasantness and goal congruence, both based on evaluations of value, to inform the utility function.

We represent utility as a multi-attribute utility function which models the trade-off between considerations of pleasantness and goal congruence as in (8), where $0 \leq \alpha \leq 1$ and in which α and $1 - \alpha$ are the relative weights given to considerations of pleasantness and goal congruence respectively.

$$\mathrm{u}\left(x_{i,j}\right) = \alpha\,\mathrm{pleas}\left(x_{i,j}\right) + \left(1-\alpha\right)\mathrm{gc}\left(x_{i,j}\right) \quad (8)$$

CBU and Decision Framing

We now show that our CBU framework can model a wide range of framing effects not previously accounted for in other computational models. Specifically, we show that CBU can account for not only traditional framing effects but also the impact of providing choice rationale and the role of domain expertise.

	Survival Frame	**Mortality Frame**
Status Quo	0 saved	0 die
Aspiration Outcome	Normal dist. centered at 200 saved	Normal dist. centered at 400 die
Expectation of Control	Normal dist. centered at 0.5	Normal dist. centered at 0.5
$\boldsymbol{\alpha}$	See Figure 2	See Figure 2

Table 1: Encoding for Asian Disease Scenario

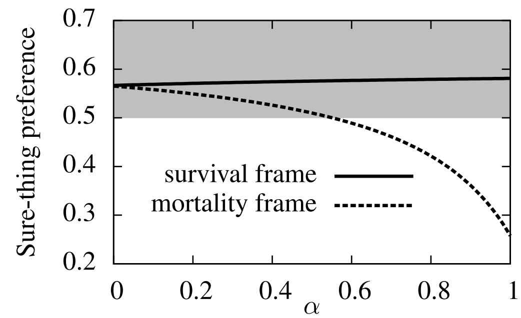


Figure 2: Asian Disease Scenario Framing using CBU

Classic Framing Effect

The Asian Disease Scenario (ADS), originally introduced by Kahneman and Tversky (1979), still remains one of the most prominent examples of the classic framing effect and is presented in its entirety in Listing 1. The original experiments demonstrated that decision makers are generally risk averse in the domain of gains (survival frame) and risk seeking in the domain of losses (mortality frame).

The decision-theoretic representation of both the survival and mortality frames is straightforward. Probabilities are described explicitly and the values of outcomes are encoded as the number of lives saved in the survival frame, e.g., "200 saved" is 200, and a negative value for the number of lives lost in the mortality frame, e.g., "600 die" is -600.

To model the scenario using CBU, we additionally specify the CBU-related variables as shown in Table 1. The ADS leaves several contextual variables underspecified with respect to our framework. Therefore, we model the distribution of the aspiration outcome as a normal distribution where the mean is the arguably rational expected value of the scenario. Specifically, this is the value associated with "200 saved" and "400 die" in the survival and mortality frames respectively. Additionally, we model the expectation of control as a normal distribution with a mean of $\frac{1}{2}$ which follows from empirical studies on expectations of control (Rotter 1975). Lastly, we interpret α, which controls the relative weight given to considerations of pleasantness and goal congruence, as being highly situational and is therefore treated as an independent variable. The plot of the resulting CBU function is shown in Figure 2 in which the x-axis models variations in α, and the y-axis corresponds to the relative strength of preference for the sure-thing alternative. The shaded area of the plot is the region in which the relative preference for the sure-thing choice *exceeds* that of the risky option.

The plot shows that the CBU framework does predict risk-averse behavior in the survival frame. However, in the mortality frame, risk-seeking behavior is not evidenced until the value of α, representative of the relative weight given to considerations of pleasantness, is sufficiently high. The consistency of preference in the survival frame is due to the proximity of the status quo and aspiration outcome which lead to similar appraisals of pleasantness and goal congruence and ultimately a risk-averse preference. Alternatively, in the mortality frame the status quo and aspiration outcome are highly differentiated which lead to conflicting appraisals and a subsequently greater variance in preference depending on the value of α. These findings echo the empirical work of Schneider (1992) showing that while preferences for risk aversion in positive frames are robust, preferences for negatively framed options, while generally risk seeking, are weak and inconsistent.

Choice Rationale

When decision makers must provide a justification for their decisions, framing effects are reduced. In a series of experiments conducted with university students involving the ADS, subjects were informed they would be providing choice rationale. While results in the survival frame were consistent with classical framing effects, i.e., majority risk-averse preferences, preferences in the mortality frame were not significantly risk seeking (Fagley and Miller 1987).

Neither CPT or SP/A Theory can explicitly account for this effect due to their one-dimensional view of framing. In both theories, the parameters controlling the behavior of the decision evaluation functions are contingent only on whether an outcome is perceived as a gain or a loss.

Within the CBU framework, we model the provision of choice rationale as an emphasis on considerations of goal congruence. Specifically, it is modeled as a reduction in α, which corresponds to a reduction in the weight associated with considerations of pleasantness and an increase in considerations of goal congruence. Therefore, a modified utility function, $\hat{\mathrm{u}}\left(x_{i,j}\right)$, as seen in (9) is employed in these situations.

$$\hat{\mathrm{u}}\left(x_{i,j}\right) = \frac{8}{10}\alpha\,\mathrm{pleas}\left(x_{i,j}\right) + \left(1 - \frac{8}{10}\alpha\right)\mathrm{gc}\left(x_{i,j}\right) \quad (9)$$

In encoding this variation of the ADS we employ the original encoding of both the outcomes and the CBU-related variables as in Table 1. The plot of the rationale-adjusted frames and the standard frames is shown in Figure 3 [1].

The plot shows that while an enhanced sense of goal congruence has no effect in the survival frame, it does play a moderating role in the mortality frame which is consistent with the original study by Fagley and Miller (1987). Additionally, our model predicts that this moderating effect is stronger when considerations of pleasantness are sufficiently high - something which we hope to explore in future work.

[1]Plots for the survival frame and the rationale-adjusted survival frame are essentially identical and therefore overlap

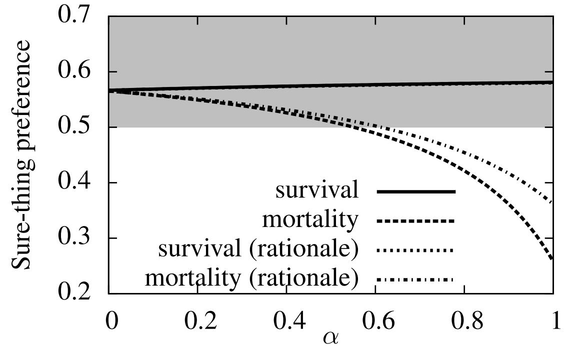


Figure 3: ADS Rationale Framing in CBU

Domain Expertise

Another framing phenomena is the resistance to framing effects shown by experts. In a study involving school psychologists and a student dropout scenario similar to the ADS, where outcomes are described as either the number of children who stay in school (positive framing) or the number that drop out (negative framing), psychologists demonstrated highly consistent risk-averse preferences when compared to control subjects (Fagley and Kruger 1986).

Both PT and SP/A are unable to account for the effect of expertise. Again, it is due to their one-dimensional view of contextual influence. And since there is no clear link between the perception of outcomes as gains or losses and decision expertise, both PT and SP/A theory are silent regarding its effect on framing.

Within the CBU model we represent expertise in a decision domain as an emphasis on considerations of goal congruence as well as differences in aspiration outcomes. These differences in aspiration are representative of the *prior* expectations expert decision makers possess and which subsequently influence other decisions based in their respective areas of expertise. In this sense, we model expertise in a manner prescribed by the Probabilistic Mental Model (PMM) Theory (Gigerenzer, Hoffrage, and Kleinbölting 1991), which posits that decision makers often make decisions based on information constructed from past, non-local, experience and knowledge. For instance, in the study involving school psychologists, we may assume that the adopted expectations of the psychologists are much *lower* than the expected value of the drop-out scenario [2].

To model decision expertise, we employ an encoding for the outcomes and CBU-related variables similarly to the ADS scenario as in Table 1. Additionally, we use the modified utility function, $\hat{\mathrm{u}}\left(x_{i,j}\right)$, in (9) to emphasize considerations of goal congruence and either a high (normal distribution centered at "400 stay in school"/"200 dropout") or low (normal distribution centered at "100 stay in school"/"500 dropout") aspiration outcome. The plot for both positive and negative frames in both conditions is shown in Figure 4.

[2]Data from the U.S. Department of Education shows that drop-out rates in the United States have declined only about 3.5% from 1972 to 1992 (McMillen 1993) which suggests that an expectation of preventing $\frac{1}{3}$ of students from dropping out is overly optimistic

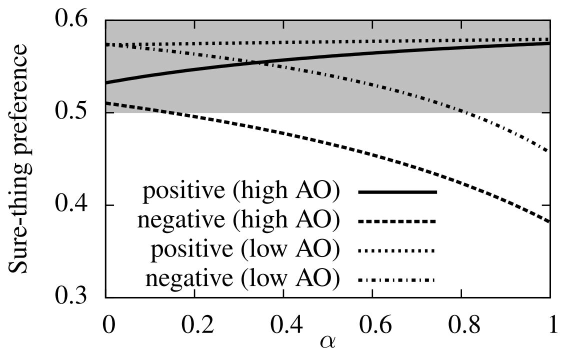


Figure 4: Dropout Expertise Framing in CBU

The results show that lower prior expectations tend to shift preferences for both frames towards risk aversion and increase consistency of choice between frames. Alternatively, adopting higher expectations shifts preferences towards risk seeking and marginally increases choice consistency. This suggests that possessing prior expectations which differ from the situational expected value may lead to a reduction in the framing effect. Moreover, while this is consistent with previous empirical research on expertise, our model also implies that the "directionality" of prior expectations are important. Specifically, they play an integral role in the overall risk preferences and the degree of choice consistency of the decision maker which has yet to be validated in empirical studies.

Conclusion

Computational models of human decision making are becoming more important in a wider range of applications. Therefore, it is vital that these models can account for a broad range of human behavior while remaining readily implementable. One well-established hallmark of human decision behavior, typically problematic for theories of choice, is the phenomenon of framing, by which the same underlying problem described differently produces different results.

Existing approaches at modeling framing treat it as a one-dimensional contextual influence and therefore lack the descriptive flexibility to account for a broad range of behavior. Therefore, we have proposed a contextually-sensitive decision framework which integrates the psychological principles of cognitive appraisal with traditional decision-theoretic approaches for modeling preferences. In particular, we have shown that appraisals of pleasantness and goal congruence can be used in a multi-attribute utility function while appraisals of control inform the weighting function.

Furthermore, by employing the CBU framework and using examples based on the classic Asian Disease Scenario and a school dropout scenario, we show that our framework is descriptively flexible enough to account not only for classical framing effects but also allow for the provision of choice rationale and domain expertise.

References

Arnold, M. 1960. *Emotion and personality*. Columbia University Press New York.

Aylett, R.; Dias, J.; and Paiva, A. 2006. An affectively-driven planner for synthetic characters. *Proceedings of ICAPS 2006*.

Bickmore, T.; Gruber, A.; and Picard, R. 2005. Establishing the computer–patient working alliance in automated health behavior change interventions. *Patient Education and Counseling* 59(1):21–30.

Bohm, P., and Lind, H. 1992. A note on the robustness of a classical framing result* 1. *Journal of Economic Psychology* 13(2):355–361.

Davidsson, P. 2001. Multi agent based simulation: beyond social simulation. *Multi-Agent-Based Simulation* 141–155.

Dias, J., and Paiva, A. 2005. Feeling and reasoning: A computational model for emotional characters. *Progress in Artificial Intelligence* 127–140.

Fagley, N., and Kruger, L. 1986. Framing effects on the program choices of school psychologists. In *Annual Meeting of the American Psychological Association, Los Angeles, CA*.

Fagley, N., and Miller, P. 1987. The effects of decision framing on choice of risky vs certain options. *Organizational Behavior and Human Decision Processes* 39(2):264–277.

Frijda, N. 2007. *The laws of emotion*. Lawrence Erlbaum Associates.

Gigerenzer, G.; Hoffrage, U.; and Kleinbölting, H. 1991. Probabilistic mental models: A brunswikian theory of confidence. *Psychological Review* 98(4):506–528.

Gratch, J., and Marsella, S. 2004. A domain-independent framework for modeling emotion. *Cognitive Systems Research* 5(4):269–306.

Highhouse, S., and Paese, P. 1996. Problem domain and prospect frame: Choice under opportunity versus threat. *Personality and Social Psychology Bulletin* 22(2):124.

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

Lazarus, R. 1991. *Emotion and adaptation*. Oxford University Press, USA.

Levin, I., and Chapman, D. 1990. Risk taking, frame of reference, and characterization of victim groups in aids treatment decisions. *Journal of Experimental Social Psychology* 26(5):421–434.

Lopes, L. 1987. Between hope and fear: The psychology of risk. *Advances in experimental social psychology* 20(3):255–295.

Marsella, S.; Johnson, W.; and LaBore, C. 2003. Interactive pedagogical drama for health interventions. In *Conference on Artificial Intelligence in Education, Sydney, Australia*. Citeseer.

McMillen, M. 1993. Dropout rates in the united states: 1992.

Ortony, A.; Clore, G.; and Collins, A. 1990. *The cognitive structure of emotions*. Cambridge Univ Pr.

Quiggin, J. 1982. A theory of anticipated utility. *Journal of Economic Behavior & Organization* 3(4):323–343.

Rickel, J.; Marsella, S.; Gratch, J.; Hill, R.; Traum, D.; and Swartout, W. 2002. Toward a new generation of virtual humans for interactive experiences. *IEEE Intelligent Systems,* 32–38.

Roseman, I. 1984. Cognitive determinants of emotion: A structural theory. *Review of Personality & Social Psychology* 5:11–36.

Rotter, J. 1966. Generalized expectancies for internal versus external control of reinforcement.

Rotter, J. 1975. Some problems and misconceptions related to the construct of internal versus external control of reinforcement. *Journal of consulting and clinical psychology* 43(1):56–67.

Scherer, K. 1982. Emotion as a process: Function, origin and regulation. *Social Science Information* 21(4-5):555.

Schneider, S. 1992. Framing and conflict: Aspiration level contingency, the status quo, and current theories of risky choice. *Journal of Experimental Psychology: Learning, Memory, and Cognition* 18(5):1040–1057.

Schoorman, F.; Mayer, R.; Douglas, C.; and Hetrick, C. 1994. Escalation of commitment and the framing effect: An empirical investigation. *Journal of Applied Social Psychology* 24(6):509–528.

Si, M.; Marsella, S.; and Pynadath, D. 2010. Modeling appraisal in theory of mind reasoning. *Autonomous Agents and Multi-Agent Systems* 20(1):14–31.

Smith, C., and Ellsworth, P. 1985. Patterns of cognitive appraisal in emotion. *Journal of personality and social psychology* 48(4):813–838.

Smith, C., and Lazarus, R. 1990. Emotion and adaptation. *Handbook of personality: Theory and research* 609–637.

Tversky, A., and Kahneman, D. 1992. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty* 5(4):297–323.