

Modeling Framing Effects: Comparing an Appraisal-Based Model with Existing Models

Jonathan Ito (ito@ict.usc.edu)

and Stacy Marsella (marsella@ict.usc.edu)

University of Southern California Institute for Creative Technologies
Playa Vista, CA 90094-2536

Abstract—One significant challenge in creating accurate models of human decision behavior is accounting for the effects of context. Research shows that seemingly minor changes in the presentation of a decision can lead to shifts in behavior; phenomena collectively referred to as *framing effects*.

This work presents a computational modeling analysis comparing the effectiveness of Context Dependent Utility, an appraisal-based approach to modeling the multi-dimensional effects of context on decision behavior, against Cumulative Prospect Theory, Security-Potential/Aspiration Theory, the Transfer of Attention Exchange model, and a power-based utility function. To contrast model performance, a non-linear least-squares analysis and subsequent calculation of Akaike Information Criterion scores, which take into account goodness of fit while penalizing for model complexity, are employed.

Results suggest that multi-dimensional models of context and framing, such as Context Dependent Utility, can be much more accurate in modeling decisions which similarly involve multi-dimensional considerations of context. Furthermore, this work demonstrates the effectiveness of employing affective constructs, such as appraisal, for the encoding and evaluation of context within decision-theoretic frameworks to better model and predict human decision behavior.

Index Terms—Cognitive simulation, appraisal, framing, context, utility, risk, human decision behavior.

I. INTRODUCTION

Computational models of human decision behavior, often referred to as descriptive models, seek to accurately model and predict the decisions that people *actually* make. Accurate, computationally-tractable descriptive models of choice are vital for modeling any decisions in which outcomes are at least partially determined by the actions of humans such as in social simulation [1], virtual-human based training [2], and interactive health-intervention [3].

Research has shown that seemingly minor changes in the presentation, or framing, of a decision problem can lead to shifts in behavior; phenomena referred to as *framing effects*. In a seminal study, Tversky and Kahneman [4] showed that outcomes framed as gains led to risk-aversion while the same outcomes framed as losses led to risk-seeking. Subsequent studies involving domains as diverse as Acquired Immune Deficiency Syndrome (AIDS) [5], taxpayer compliance [6], and judgments of website quality [7] have also demonstrated framing effects to varying degrees. In addition to gains and losses, framing can involve the perception of concerns as diverse as the role [8] and the needs [9] of the decision maker.

Despite the multi-dimensional nature of context, the prevalence of framing effects in many domains, and the impact they have on the decision process, few decision models address explicitly the multi-dimensional impact of context on decisions. Furthermore, existing approaches which do address framing are generally limited by a one-dimensional view of context. For instance, Prospect Theory [10] models the effect of context only to the extent that it applies to outcomes perceived as either gains or losses. Recent work however, has developed an appraisal-based approach for modeling the multi-dimensional effect of context on decision behavior. This approach, referred to as Context Dependent Utility (CDU) [11], relies on a decision-theoretic implementation of concepts in Appraisal Theory for the contextually-sensitive interpretation of a decision scenario. Appraisal Theory addresses the process by which emotions arise from an evaluation, or *appraisal*, of the personal significance of the circumstances confronting an individual [12]–[15]. CDU hinges on the assumption that appraisal dimensions such as pleasantness, goal congruence, and control, traditionally employed to differentiate emotions, are also instrumental in capturing the salient contextual aspects of a situation which subsequently may affect decision behavior.

This work seeks to compare the effectiveness and descriptive accuracy of CDU against decision models adhering to a more traditional one-dimensional view of context. In particular, this work presents the results of a computational modeling analysis comparing the effectiveness of Context Dependent Utility [11], Cumulative Prospect Theory [16], Security-Potential/Aspiration Theory [17]–[19], Transfer of Attention Exchange [20], and a power-based utility function. To contrast model performance, a non-linear least-squares analysis and the subsequent calculation and evaluation of Akaike Information Criterion (AIC) [21] scores, which take into account goodness of fit while penalizing for model complexity, are employed.

II. METHOD

This work presents a computational modeling analysis comparing the effectiveness of a power-based utility function (POW), Context Dependent Utility (CDU) [11], Cumulative Prospect Theory (CPT) [16], Security-Potential/Aspiration Theory (SP/A) [17]–[19], and Transfer of Attention Exchange (TAX) [20]. A non-linear least-squares analysis is used to fit the candidate models to data from an experimental framing

study in which participants were asked to decide between competing plans to prevent school dropouts. Furthermore, to ensure the best possible fit for each candidate model, a variety of initial parameter values are employed in the fitting process to avoid local minima. Akaike Information Criterion (AIC) [21] scores for each candidate model are then computed and evaluated to determine the most effective model. In particular, AIC provides a complete ranking of candidate models according to their ability to fit the data while also imposing a penalty based on the number of model parameters to avoid overfitting, reward simplicity, and allow for a more balanced comparison between disparate models. Additionally, model selection using AIC has been shown to be asymptotically equivalent, i.e., approximately equivalent in the long-run, to cross-validation [22], [23], another popular model selection technique.

A. Participants, Procedure, and Design

For the study, 525 participants from the United States were recruited through Amazon Mechanical Turk. Each participant received \$0.40 for participation. The self-reported gender distribution was 319 male (61%) and 206 female (39%). The median age range was 22 to 34 years with 85% of participants below 45 years of age. The majority of participants self-identified as white (78%). Approximately half of participants (50%) have also completed a 2 year college degree or higher.

The study was administered as an anonymous online questionnaire based on a study designed by Fagley, et al. [24] to test gain-loss framing, but subsequently expanded to include additional considerations of context. Participants were presented with two plans to prevent 1000 at-risk students from dropping out: one plan results in 400 of the 1000 students dropping out and is considered the risk-averse plan since the outcome is guaranteed whereas the other plan results in a 40% chance that *all* students drop out and a 60% chance that *no* students drop out and is considered the more risky plan.

Framing involved the manipulation of context associated with considerations of pleasantness, goal congruence, and control. The manipulation of pleasantness was accomplished through the description of outcomes as gains (pleasant) or losses (unpleasant). In particular, in the loss condition, outcomes were described by the number of students that drop out; for the gain condition, outcomes were described by the number of students that stay in school; for the neutral condition, outcomes were described using both the number of students that drop out and stay in school.

The manipulation of goal congruence was based on a study conducted by Payne, et al. [25] and involved informing participants that their performance would be evaluated in comparison to the average retention rate, i.e., the percentage of students at-risk of dropping out that are retained, of other schools in the district. Therefore, in the low retention condition the expected retention rate was 5% (50 of the 1000 at-risk students stay in school); in the neutral retention condition the retention rate was 40% (400 of the 1000 at-risk students stay in school);

TABLE I
NUMBER OF PARTICIPANTS PER CONDITION

Gain/Loss	Retention Rate	Source of Uncertainty		
		Chance	Neutral	Ability
Loss	Low	20	18	23
	Neutral	20	26	18
	High	26	23	22
Neutral	Low	20	18	17
	Neutral	21	21	21
	High	21	22	19
Gain	Low	20	19	15
	Neutral	15	17	20
	High	13	16	14

and in the high retention condition the expected rate was 75% (750 of the 1000 at-risk students stay in school).

The manipulation of control, derived from research on loci of control [26], involved depicting the source of uncertainty in the risky plan as either arising from chance events which are perceived as relatively uncontrollable or from the ability of the decision maker, perceived as being relatively more controllable. Therefore, in the chance condition, the uncertainty in the risky plan was depicted as arising from the random selection, i.e., lottery, of funding applications; In the ability condition, the source of uncertainty in the risky plan was described as arising from the hypothetical ability of the participant to write a persuasive funding application; and the neutral condition involved a mixture of the two.

The study was conducted as a 3x3x3 between-subjects factorial in which both the presentation order of the two dropout prevention plans and the ordering of the two potential outcomes of the risky alternative were balanced. The primary dependent variable in the decision task was a 7-point strength-of-preference response which included an option indicating indifference. Table I illustrates the various factors and the number of participants that were assigned to each combination of factors.

B. Approaches to Modeling Framing Effects

The goal of the computational modeling analysis was to compare the effectiveness of several competing approaches for modeling decision preferences across distinct contextual settings. In particular, a power utility function (POW), Context Dependent Utility (CDU) [11], Cumulative Prospect Theory (CPT) [16], Security-Potential/Aspiration (SP/A) Theory [17]–[19], and Transfer of Attention Exchange (TAX) [20] were compared.

1) *Power Utility (POW)*: The power utility model is a one-parameter model of preference under risk and is insensitive to variations in context. It calculates the utility of an action G , seen in (1), in which G may be described as the n -tuple, $G = (p_1, v_1, \dots, p_n, v_n)$, such that v_i is the value of the i th outcome, p_i is the probability that the i th outcome occurs given action G , and $\sum_1^n p_i = 1$. While the power utility model does not explicitly account for considerations of context, it can model general risk tendencies. In particular, when $k < 1$,

decision behavior is characterized as risk-averse; when $k > 1$, decision behavior tends towards risk-seeking; and when $k = 1$, decision behavior is risk-neutral.

$$POW(G) = \sum_{i=1}^n p_i v_i^k \quad (1)$$

An additional function is also required to associate the values of the power utility evaluation for the sure and risky alternatives to the strength-of-preference measure captured in the experimental data. Therefore, the Luce Choice Rule [27] is employed as in (2) in which the strength of preference for the sure plan under the power utility model, $SURE_{POW}$, is a function of the utility of the sure plan, $POW(SURE)$, and the risky plan, $POW(RISKY)$. The simplified choice function for the school dropout scenario is shown in 3.

$$SURE_{POW} = \frac{POW(SURE)}{POW(SURE) + POW(RISKY)} \quad (2)$$

$$= \frac{0.4^k}{0.4^k + 0.4} \quad (3)$$

2) *Context Dependent Utility (CDU)*: Context Dependent Utility integrates appraisal with a rank-dependent utility formalization to model the contextually-sensitive interpretation and evaluation of a decision scenario [11]. According to CDU, the contextually-sensitive utility of an action G , in which G is comprised of probability-outcome pairs in ascending order of outcome value, is shown in (4). Furthermore, the utility value over individual outcomes is a linear weighting between considerations of pleasantness and goal congruence as seen in (5) whereas the decumulatively-defined weighting function involves considerations of control as seen in (6), (7), and (8).

$$CDU(G) = \sum_{i=1}^n \pi_i u(v_i) \quad (4)$$

$$u(v_i) = (\beta pleas(v_i) + (1 - \beta) gc(v_i)) \quad (5)$$

$$n_i = \begin{cases} w(D_i) & w(D_{i+1}) & \text{if } i < n \\ w(D_i) & & \text{if } i = n \end{cases} \quad (6)$$

$$w(D_i) = a(ctrl(D_i)) + b \quad (7)$$

$$D_i = \sum_{j=i}^n p_j \quad (8)$$

The appraisals of pleasantness, goal congruence, and control are defined identically as functions of diminishing sensitivity made with respect to reference points as in (9). In particular, pleasantness is an evaluation of value made with respect to the value of the status quo as in (10); goal congruence is an evaluation of value made with respect to the value of the aspiration outcome as in (11); and control is an evaluation of decumulative probability made with respect to the probability of the control threshold as in (12).

Experimental Factor	Level	Encoding
Gain-Loss Description (Pleasantness & Status Quo)	Loss	$v_{sq} = 1:00$
	Neutral	$v_{sq} = 0:40$
	Gain	$v_{sq} = 0:00$
Retention Rate (Goal Congruence & Aspiration Outcome)	Low	$v_{ao} = 0:05$
	Neutral	$v_{ao} = 0:40$
	High	$v_{ao} = 0:75$
Source of Uncertainty (Control & Control Threshold)	Chance	$p_{ct} = 1:00$
	Neutral	$p_{ct} = 0:50$
	Ability	$p_{ct} = 0:00$

TABLE II
EXPERIMENT 1 REFERENCE POINT ENCODING

$$appraise(x, ref, k) = \begin{cases} (x - ref)^k & \text{if } x - ref \geq 0 \\ (ref - x)^k & \text{if } x - ref < 0 \end{cases} \quad (9)$$

$$pleas(v_i) = appraise(v_i, v_{sq}, k_{pleas}) \quad (10)$$

$$gc(v_i) = appraise(v_i, v_{ao}, k_{gc}) \quad (11)$$

$$ctrl(D_i) = appraise(D_i, p_{ct}, k_{ct}) \quad (12)$$

The reference points, i.e., status quo, aspiration outcome, and control threshold, for the school dropout scenario are encoded as in Table II. The high and low values of the status quo reflect the presentation of outcomes as either losses (number dropping out) or gains (number staying in school). For the neutral status quo condition, a value of 0.4 was chosen to reflect the expected value of the scenario. The aspiration outcome values follow directly from the description of the evaluation criteria. The control threshold value for the chance condition was chosen such that all outcome probabilities would not exceed it and be perceived as uncontrollable. Alternatively, the control threshold value for the ability condition was chosen such that all outcome probabilities would exceed it and be perceived as controllable.

Action selection is implemented using Luce's choice rule in which the utility for the sure outcome is raised to the power k such that $0 < k < 1$ models a tendency towards risk-aversion, whereas $k > 1$ models a tendency towards risk-seeking. For the school dropout scenario the choice function is simplified as seen in 13. Furthermore, to facilitate the fitting process, the parameter β , governing the weight given to considerations of pleasantness over goal congruence is set to $\frac{1}{2}$.

$$STR_{CDU} = \frac{u(0.4)^k}{u(0.4)^k + ctrl(0.4)} \quad (13)$$

3) *Cumulative Prospect Theory (CPT)*: Cumulative Prospect Theory [16] extends Prospect Theory [10] by utilizing a rank-dependent formalization to resolve violations of stochastic dominance which arise from the subcertainty of its weighting function. The general form of the CPT calculation is given in (14) in which the probability-outcome pairs of action G are in ascending order of value such that negative subscripts denote negative outcomes, positive subscripts denote positive outcomes, and the neutral outcome v_0 occurs with probability p_0 .

$$CPT(G) = \sum_m^n \pi(p_i) u(v_i) \quad (14)$$

The CPT utility function for individual outcomes is given in (15) in which $0 < \alpha \leq 1$, $0 < \beta \leq 1$, and $\lambda > 1$ are required to ensure that the utility function is one of diminishing returns from the reference point and that losses loom larger than gains.

$$u(v) = \begin{cases} v^\alpha & \text{if } v \geq 0 \\ \lambda (v)^\beta & \text{if } v < 0 \end{cases} \quad (15)$$

The weighting function of CPT is decumulative for gains and cumulative for losses as seen in (16). Furthermore, the weighting function adheres to the principle of diminishing sensitivity with respect to the reference points of certainty, $p = 1$, and impossibility, $p = 0$. The weighting functions for gains and losses are shown respectively in (17) and (18) such that $0 < \gamma \leq 1$ and $0 < \delta \leq 1$.

$$\pi(p_i) = \begin{cases} w^+(p_i) & \text{if } i = n \\ w^-(p_i) & \text{if } i = m \\ \begin{cases} w^+(p_i + \dots + p_n) \\ w^+(p_{i+1} + \dots + p_n) \end{cases} & \text{if } 0 \leq i < n \\ \begin{cases} w^-(p_m + \dots + p_i) \\ w^-(p_m + \dots + p_{i-1}) \end{cases} & \text{if } m < i \leq 0 \end{cases} \quad (16)$$

$$w^+(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{\frac{1}{\gamma}}} \quad (17)$$

$$w^-(p) = \frac{p^\delta}{(p^\delta + (1-p)^\delta)^{\frac{1}{\delta}}} \quad (18)$$

According to CPT, outcomes must be *coded*, i.e., denoted as gains or losses, with respect to some reference point. However, CPT provides little guidance regarding both the determination of the reference point and the coding process. Therefore, the reference point is implemented as a linear weighting between the status quo and aspiration outcome values as specified in Table II mediated by k , such that $0 \leq k \leq 1$, as seen in (19). Furthermore, the coding process is implemented as the difference between the uncoded outcome value and the value of the reference point, v_{ref} .

$$v_{ref} = kv_{sq} + (1-k)v_{ao} \quad (19)$$

The Luce Choice Rule is employed to transform CPT values to the strength-of-preference measures. The decision function is simplified for the school dropout data as seen in 20. Furthermore, the parameter δ is discarded in the fitting process since only the weight of the best outcome, guaranteed to be positive, is evaluated. Additionally, to ensure the convergence of the fitting process, the parameter γ is fixed at 0.55.

$$SURL'_{CPT} = \frac{u(1 - v_{ref})}{u(1 - v_{ref}) + w^+(0.4)} \quad (20)$$

4) *Security-Potential/Aspiration Theory (SP/A)*: Security-Potential/Aspiration (SP/A) Theory is a dual-criteria function modeling the tradeoff between security-minded (risk-averse) attitudes and potential-minded (risk-seeking) attitudes and the role of aspiration-level considerations [17]–[19]. The SP/A function is shown in (21), in which the action G is comprised of probability-outcome pairs in ascending order of value.

$$SPA(G) = f(SP(G), A(G)) \quad (21)$$

The Security-Potential (SP) criterion is a variant of Rank-Dependent Utility [28], as seen in (22), with the simplifying assumption that outcome utility is its value, i.e., $u(v) = v$.

$$SP(G) = \sum_{i=1}^n \pi(p_i) v_i \quad (22)$$

The weighting component, $\pi(p_i)$, is defined decumulatively as in (23). According to previous work on SP/A and framing [29], the variables controlling the weighting function may vary depending on the perception of outcomes as gains or losses. In particular, the weighting function, as in (24) and (25), is defined such that h^+ and h^- are respectively the weightings for gains and losses. Gains are defined as outcomes with values meeting or exceeding the status quo value, as specified in Table II, and losses are outcomes with values less than the status quo value. Additionally, the variables q_s and q_p control the intensity of the *security* and *potential* evaluations respectively such that $q_s \leq 0$ and $q_p \leq 0$.

$$\pi(p_i) = \begin{cases} w^+(p_n) & \text{if } v_i \geq v_{sq}, i = n \\ w^+(p_i + \dots + p_n) & \text{if } v_i \geq v_{sq}, i < n \\ w^-(p_n) & \text{if } v_i < v_{sq}, i = n \\ w^-(p_i + \dots + p_n) & \text{if } v_i < v_{sq}, i < n \end{cases} \quad (23)$$

$$w^+(p) = h^+ p^{q_s + 1} + (1 - h^+) \left(1 - (1 - p)^{q_p + 1}\right) \quad (24)$$

$$w^-(p) = h^- p^{q_s + 1} + (1 - h^-) \left(1 - (1 - p)^{q_p + 1}\right) \quad (25)$$

The aspiration criterion is the cumulative probability that a particular action results in an outcome which meets or exceeds the aspiration value, v_{asp} , as specified in Table II. The criterion is defined in (26), where i_{asp} is the index of the first outcome to meet or exceed the value of the aspiration outcome.

$$A(G) = \sum_{i=i_{asp}}^n p_i \quad (26)$$

Based on previous studies [29], the SP and A criteria are evaluated individually and then linearly combined. The choice function for the SP criterion, $SURE_{SP}$, is implemented using Luce's choice rule while the choice function for the A criterion, $SURE_A$ is given in (27) for gains and (28) for losses. The combined choice function is implemented as a weighted linear mixture of the individual choice rules as given in (29).

$$SURE_{A^*} = \frac{A(SURE)^{t^*}}{A(SURE)^{t^*} + A(RISKY)^{t^*}} \quad (27)$$

$$SURE_A = \frac{(1 - A(RISKY))^t}{(1 - A(SURE))^t + (1 - A(RISKY))^t} \quad (28)$$

$$SURE_{SPA} = kSURE_{SP} + (1 - k)SURE_A \quad (29)$$

The simplified choice function for the school dropout scenario is shown in (30). Furthermore, the assumption that $q^p = q^s = 1$ is made to facilitate the fitting process.

$$SIR_A = \begin{cases} SIR_A^+ & \text{if } sq \leq 0.4 \\ SIR_A^- & \text{if } sq > 0.4 \end{cases} \quad (30)$$

$$SIR_{SPA} = \frac{0.4k}{0.4 + w^+(0.4)} + ((1 - k)SIR_A) \quad (30)$$

5) *Transfer of Attention Exchange (TAX)*: In the TAX model the value of an action is a weighted average of the utility of each outcome in which the weights represent transfers of attention from one branch to another [20]. The full TAX function is given in (31), in which outcomes are arranged in descending order of preference, i.e., $v_i \geq v_{i+1}$. Additionally, the attention-transfer function, ω , is defined according to the "special" TAX model [30], [31] as shown in (32).

$$TAX(G) = \frac{\sum_{i=1}^n t(p_i) u(v_i)}{\sum_{i=1}^n t(p_i)} + \frac{\sum_{i=1}^n \sum_{k=1}^i [u(v_i) - u(v_k)] \omega(p_i, p_k, n)}{\sum_{i=1}^n t(p_i)} \quad (31)$$

$$\omega(p_i, p_k, n) = \begin{cases} \frac{\delta t(p_k)}{n+1} & \text{if } \delta > 0 \\ \frac{\delta t(p_i)}{n+1} & \text{if } \delta \leq 0 \end{cases} \quad (32)$$

The TAX model assumes consequences are evaluated relative to some reference point rather than as absolute states. Therefore, since TAX does not explicitly describe how the reference point is determined, a linear weighting model is adopted as in (33) in which k mediates the weighting between the status quo and the aspiration outcome values as specified in Table II. Furthermore, consequence values are coded relative to the reference point as $v_i - v_{ref}$ such that the resulting utility function, implemented as a power function conditioned on whether outcomes are perceived as gains or losses, is shown in (34). The probability-weighting function $t(p_i)$ is implemented as a power function as suggested in [32] and seen in (35)

Model	Parameter	Value
POW	k	00:72
	\square	00:92
CPT	\square	00:52
	\square	01:68
	k	00:02
SP/A	h^+	00:63
	t^+	15:00
	t	15:00
	k	00:82
TAX	\square	00:64
	\square	00:70
	k	00:01
CDU	k_{pleas}	00:66
	k_{gc}	00:25
	k_{ctrl}	00:81
	k	00:73

TABLE III
PARAMETER ESTIMATES

Model	K	RSS	AIC	Δ_i	w_i
CDU	4	38:34	126:0	0:0	0:83
CPT	4	38:64	130:1	4:1	0:11
SP/A	4	38:72	131:2	5:1	0:06
TAX	3	39:31	137:1	11:1	3:19 \square 10 ⁰³
POW	1	42:63	175:7	49:7	1:34 \square 10 ¹¹

TABLE IV
AIC SUMMARY FOR CANDIDATE MODELS

$$ref = kv_{sq} + (1 - k)v_{ao} \quad (33)$$

$$u(v_i, ref) = \begin{cases} (v_i - ref)^\beta & \text{if } v_i - ref \geq 0 \\ (ref - v_i)^\beta & \text{if } v_i - ref < 0 \end{cases} \quad (34)$$

$$t(p_i) = p_i^\gamma \quad (35)$$

The simplified TAX calculations for both the sure and risky alternative of the school dropout scenario are shown in (36) and (37) respectively.

$$TAX(SURE) = u(0.4, ref) \quad (36)$$

$$TAX(RISKY) = \frac{t(0.4) \frac{\delta t(0.4)}{3}}{t(0.4) + t(0.6)} \quad (37)$$

C. Results and Discussion

The nonlinear least-squares analysis yielded the parameter estimates as seen in Table III for all candidate models. The number of parameters (K), residual sum of squares (RSS), AIC score (AIC), difference from the minimum AIC score (Δ_i), and Akaike weight (w_i), which gives the relative likelihood that model i best fits the data, are given in Table IV.

Results suggest that CDU provides the best overall fit of the data as evidenced by the lowest RSS, a measure of discrepancy between the data and the estimation model, among candidate models. Furthermore, AIC scores, which provide for an unbiased comparison between models with disparate number of parameters through penalizing models with more parameters (since additional parameters presumably result in a better fit), suggest that CDU is still more effective than models with less parameters such as TAX and POW. In particular,

CDU is approximately 7.5 times more likely than CPT to most accurately model the school dropout prevention data when considering AIC values. These results suggest that multi-dimensional models of context and framing, such as CDU, can be much more accurate in modeling human decision behavior when the context of a decision is similarly complex and multi-dimensional in nature.

III. CONCLUSION

One significant challenge in creating accurate, descriptive models of human behavior is accounting for the effect of context on decision behavior. Existing approaches at modeling context and its effects on decision behavior, i.e, framing effects, are generally limited by a one-dimensional view of contextual influence and therefore lack the descriptive flexibility to account for a broad range of behavior.

Therefore, this work compares the effectiveness of a decision framework relying on appraisal to model the multi-dimensional effect of context on decision behavior against decision models adhering to a more traditional one-dimensional view of context predicated on the perception of outcomes as gains or losses. Specifically, this work presents a computational modeling analysis comparing the effectiveness of a power-based utility function, Context Dependent Utility [11], Cumulative Prospect Theory [16], Security-Potential/Aspiration Theory [17]–[19], and Transfer of Attention Exchange [20] in modeling multi-dimensional framing effects involving considerations of pleasantness, goal congruence, and control within a school dropout prevention scenario.

Through the process of fitting and the subsequent calculation and comparison of AIC scores, the results show that Context Dependent Utility outperforms the other candidate models by a factor of approximately 7.5. In sum, the present study illustrates the need for models which represent explicitly the multi-dimensional effect of context on behavior, such as Context Dependent Utility, especially when modeling decision behavior across contextually distinct situations. Furthermore, this work demonstrates the efficiency of employing affective constructs, such as appraisal, for the encoding and evaluation of context within decision-theoretic frameworks to better model and predict human decision behavior.

REFERENCES

- [1] P. Davidsson, "Multi agent based simulation: beyond social simulation," *Multi-Agent-Based Simulation*, pp. 141–155, 2001.
- [2] J. Rickel, S. Marsella, J. Gratch, R. Hill, D. Traum, and W. Swartout, "Toward a new generation of virtual humans for interactive experiences," *IEEE Intelligent Systems*, pp. 32–38, 2002.
- [3] T. Bickmore, A. Gruber, and R. Picard, "Establishing the computer-patient working alliance in automated health behavior change interventions," *Patient Education and Counseling*, vol. 59, no. 1, pp. 21–30, 2005.
- [4] A. Tversky and D. Kahneman, "The framing of decisions and the psychology of choice," *Science*, vol. 211, no. 4481, p. 453, 1981.
- [5] I. Levin and D. Chapman, "Risk taking, frame of reference, and characterization of victim groups in aids treatment decisions," *Journal of Experimental Social Psychology*, vol. 26, no. 5, pp. 421–434, 1990.
- [6] H. Liu, Q. Xia, and J. Xu, "Taxpayer compliance in china: A prospect theory analysis," in *Artificial Intelligence, Management Science and Electronic Commerce (AIMSEC), 2011 2nd International Conference on*. IEEE, 2011, pp. 1292–1291.
- [7] J. Hartmann, A. De Angeli, and A. Sutcliffe, "Framing the user experience: information biases on website quality judgement," in *Proceedings of the twenty-sixth annual SIGCHI conference on Human factors in computing systems*. ACM, 2008, pp. 855–864.
- [8] W. Wagenaar, G. Keren, and S. Lichtenstein, "Islanders and hostages: Deep and surface structures of decision problems* 1," *Acta Psychologica*, vol. 67, no. 2, pp. 175–189, 1988.
- [9] S. Mishra and L. Fiddick, "Beyond gains and losses: The effect of need on risky choice in framed decisions," *Journal of personality and social psychology*, vol. 102, no. 6, p. 1136, 2012.
- [10] D. Kahneman and A. Tversky, "Prospect theory: An analysis of decision under risk," *Econometrica*, vol. 47, no. 2, pp. 263–291, 1979.
- [11] J. Ito and S. Marsella, "Contextually-based utility: An appraisal-based approach at modeling framing and decisions," in *Twenty-Fifth AAAI Conference on Artificial Intelligence*, vol. 2, 2011, pp. 60–65. [Online]. Available: <http://ict.usc.edu/ito/ito2011contextually.pdf>
- [12] M. Arnold, *Emotion and personality*. Columbia University Press New York, 1960.
- [13] I. Roseman and C. Smith, "Appraisal theory: Overview, assumptions, varieties, controversies," *Appraisal processes in emotion: Theory, methods, research*, pp. 3–19, 2001.
- [14] K. Scherer, "On the sequential nature of appraisal processes: Indirect evidence from a recognition task," *Cognition & Emotion*, vol. 13, no. 6, pp. 763–793, 1999.
- [15] A. Ortony, G. Clore, and A. Collins, *The cognitive structure of emotions*. Cambridge Univ Pr, 1990.
- [16] A. Tversky and D. Kahneman, "Advances in prospect theory: Cumulative representation of uncertainty," *Journal of Risk and uncertainty*, vol. 5, no. 4, pp. 297–323, 1992.
- [17] L. Lopes, "Between hope and fear: The psychology of risk," *Advances in experimental social psychology*, vol. 20, no. 3, pp. 255–295, 1987.
- [18] —, "Re-modeling risk aversion: A comparison of bernoullian and rank dependent value approaches," *Acting under uncertainty: Multidisciplinary conceptions*, pp. 267–99, 1990.
- [19] —, "Algebra and process in the modeling of risky choice," *Psychology of Learning and Motivation*, vol. 32, pp. 171–220, 1995.
- [20] M. Birnbaum and A. Chavez, "Tests of theories of decision making: Violations of branch independence and distribution independence," *Organizational Behavior and Human Decision Processes*, vol. 71, no. 2, pp. 161–194, 1997.
- [21] H. Akaike, "A new look at the statistical model identification," *Automatic Control, IEEE Transactions on*, vol. 19, no. 6, pp. 716–723, 1974.
- [22] M. Stone, "An asymptotic equivalence of choice of model by cross-validation and akaike's criterion," *Journal of the Royal Statistical Society. Series B (Methodological)*, pp. 44–47, 1977.
- [23] Y. Fang, "Asymptotic equivalence between cross-validations and akaike information criteria in mixed-effects models," *Journal of Data Science*, vol. 9, pp. 15–21, 2011.
- [24] N. Fagley, P. Miller, and R. Jones, "The effect of positive or negative frame on the choices of students in school psychology and educational administration," *School Psychology Quarterly*, vol. 14, no. 2, pp. 148–162, 1999.
- [25] J. Payne, D. Laughhunn, and R. Crum, "Further tests of aspiration level effects in risky choice behavior," *Management Science*, pp. 953–958, 1981.
- [26] J. Rotter, "Generalized expectancies for internal versus external control of reinforcement," 1966.
- [27] R. Luce, *Individual choice behavior*. Wiley New York, 1959.
- [28] J. Quiggin, "A theory of anticipated utility," *Journal of Economic Behavior & Organization*, vol. 3, no. 4, pp. 323–343, 1982.
- [29] L. Lopes and G. Oden, "The role of aspiration level in risky choice: A comparison of cumulative prospect theory and sp/a theory," *Journal of mathematical psychology*, vol. 43, no. 2, pp. 286–313, 1999.
- [30] M. Birnbaum, "Paradoxes of allais, stochastic dominance, and decision weights," *Decision science and technology: Reflections on the contributions of Ward Edwards*, pp. 21–52, 1999.
- [31] M. Birnbaum and S. Stegner, "Source credibility in social judgment: Bias, expertise, and the judge's point of view," *Journal of Personality and Social Psychology*, vol. 37, no. 1, p. 48, 1979.
- [32] M. Birnbaum, "New paradoxes of risky decision making," *Psychological Review*, vol. 115, no. 2, p. 463, 2008.