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Emotion as a Tradeable Quantity

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ABSTRACT

Three studies investigate how physiological emotional responses can be combined with symbolic information to predict preferences. The first study used a weighted proportional difference rule to combine explicitly quantified symbolic and emotional information. The proportion of emotion model was more predictive than a simple additive emotional (AE) combination in decisions about selecting dating partners. Study 2 showed that a simple proportion algorithm of emotionally derived weights and a simple AE model predicted preference equally well for decisions between equal expected value (EV) gambles. Study 3 provided additional evidence for decision mechanisms that combine physiological measures within symbolic trade-off algorithms for choices between diamond rings. Self-reported emotion measures proved to be better predictors than physiological measures. The results are discussed in the context of other major models of emotional influence on preference and provide a foundation for future research on emotional decision-making mechanisms. Copyright © 2008 John Wiley & Sons, Ltd.

KEY WORDS emotion; decision-making; preference

INTRODUCTION

Lay reasoning on the benefits of emotion in decision-making is Janus-faced. Advice abounds to "listen to your heart" and "trust your gut feeling," contrasting admonishments to not "let your heart cloud your mind" nor "let your emotions get the best of you." While contradictory, each of these pieces of decision advice can be compelling depending on the situation.

The debate on the benefit of emotion in choice extends to the scientific literature. Emotion-based decision-making has been viewed as irrational and has been largely ignored in the economic literature (Elster, 1998). However, recent psychological research has revealed that actual preferences are dependent on the emotions experienced and anticipated by decision makers (Bechara, Damasio, Tranel, & Damasio, 1997; Mellers, 2000; Slovic, Finucane, Peters, & MacGregor, 2002). This paper attempts to extend previous work on the role of emotion in choice by suggesting specific mechanisms by which emotion creates value for the

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decision maker. We demonstrate how emotion can be combined with explicit symbolic information in a decision-making algorithm to predict choices by trading proportions as common currency. Furthermore, we demonstrate that physiological measures of arousal can serve as attribute values in a decision-making algorithm and improve choice prediction over purely cognitive models.

We propose that the role of emotion is twofold. First, emotion is hypothesized to index attribute values of choice alternatives that are not explicitly quantified. For example, the color of a car, the location of a job, or the physical attractiveness of a potential dating partner, are all attributes that give rise to affective reactions of liking or disliking. Second, emotion is also assumed to reflect the weight a decision maker places on attribute values or options. These notions are tested using both physiological and self-reported measures of emotion in both certain and risky situations.

Emotion-based theories of behavior

Theory on the functional nature of emotions has suggested that emotions act as regulators of information processing (Cosmides & Tooby, 2000). This view is consistent with Damasio's (1994) theoretical stance that one of the functions of emotion is to guide the organism in choosing a specific behavior. Damasio (1994) developed the *somatic marker hypothesis* which suggests we possess a valence-flagging device that efficiently eliminates choice options, by either associating alarms with potentially negative alternatives, or engendering magnetism toward potentially positive alternatives (but see Maia & McClelland, 2004).

In a related vein, researchers have proposed that affective reactions serve as information to other judgments, that is, the affect-as-information hypothesis (Schwarz & Clore, 1983). Numerous studies provide evidence of the informative and behaviorally directive properties of emotion. An early study on this topic found that manipulating moods affected life satisfaction ratings (Schwarz & Clore, 1983). Expanding on this conception, Ortony, Clore, and Collins (1988) proposed a model of emotion called the cognitive structure of emotion in which emotion is defined as a valenced degree of arousal experienced in response to some stimulus. Further, the authors suggest that emotions are the informational output of an appraisal process via which the organism becomes aware of the value of the object or event in the environment. In addition, emotion is not only seen as informative in terms of the valence of an appraisal, but it also functions as a meaningful interpretation of the *degree* of that valence (i.e., degree of like or dislike, pleasure or displeasure, etc.). The intensity of an emotion is dependent on how salient the appraisal of a situation is to an organism. The more important an appraisal is for the goals of the organism, the more intense is the resulting affective experience (Clore & Ketelaar, 1997). In the same light, Frijda (1994) has coined the term 'relevance signaling mechanisms' to describe the function of emotions. Emotions signal the relevance of objects or events to the concerns of an organism in any given situation, so that the cognitive and action systems can respond appropriately to the evaluation. The intensity of emotion is dependent on what is important to the organism (Frijda, Ortony, Sonnemans, & Clore, 1992; Frijda, 1993; Sonnemans & Frijda, 1995).

Emotion-based theories in decision-making

The decision-making literature has paid increasing attention to the role of emotion in judgments and choices. The ''how-do-I-feel-about-it'' (HDIF) heuristic stemmed from the affect as information hypothesis of Schwarz and Clore (1983) and proposes that individuals guide their judgments and choices from the appraisal of their feelings. When individuals use this heuristic, an object or event is held as a representation in the mind and the appraisal (''how do I feel about it?'') is completed (Pham, 1998). Similarly, Finucane, Alhakami, Slovic, and Johnson (2000) have proposed an ''affect heuristic'' that plays an important role in the assessment of risk. Use of the heuristic suggests that we reference a readily available overall affective impression of an alternative in a given decision situation, and the reliance on this affective impression increases decision efficiency.

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Focusing on satisfaction and choice preferences, Mellers and colleagues developed and tested two models. First, decision affect theory (Mellers, Schwartz, Ho, & Ritov, 1997) synthesized theories on the minimization of regret (Bell, 1982; Loomes & Sugden, 1982) and disappointment (Bell, 1985; Loomes and Sugden, 1986) and the maximization of elation into a model that successfully accounts for the emotional response to outcomes of gambles. Next, the authors developed subjective expected pleasure (SEP) theory to model risky choices (Mellers, Schwartz, & Ritov, 1999). This model proposes that decision makers balance the anticipated pleasures and pains of one gamble against the anticipated pleasures and pains of a second gamble. It weights the expected emotional response from the positive and negative outcomes of a gamble by the subjective probability of their occurrence. The gamble with the greatest positive weighted emotional response is chosen. In a comparative analysis, the authors compared SEP with subjective expected utility (SEU) theory (Savage, 1954) which is a special case of SEP. The results revealed that SEP accounted for variance above and beyond SEU (Mellers et al., 1999).

The current research advances upon these models by testing how physiological measures of experienced emotion during choice tasks can be combined quantitatively with ‘‘colder’’ symbolic information in a decision-making algorithm to predict preferences.

Incorporating emotions in choice models[1]

A main goal of our work is to test emotional reactions as quantitative inputs in decision algorithms. We attempt to specify, at a granular level, the mechanisms that combine emotions with cognitive assessments to influence preferences.

We begin with the proportional difference model (PD) of choice proposed by González-Vallejo (2002) and modify it in order to provide an algorithm of combining emotional and symbolic information. The PD model is a special case of the stochastic PD that was developed to describe choice propensities of individual decision makers and address violations of normative SEU axioms. In addition, the model has been successfully used to account for the reflection effect (González-Vallejo, Reid, & Schlitz, 2003) and for choices in decisions under certainty involving consumer products (González-Vallejo & Reid, 2006).

PD is a stochastic model that assumes that decision makers solve the problem of competing goals by focusing on attribute differences that proportionally accrue to produce advantages (disadvantages) and ultimately dictate a propensity toward a course of action. The model stipulates that a simple difference mechanism underlies choices that require comparisons on different units (e.g., of price and quality) via a standardization of differences. More specifically, let A and B be two options defined as $A=(a, p)$ and $B=(b, q)$, where $\{a, b\}$ are values of dimension X and $\{p, q\}$ are values of a second dimension Y. A decision maker is attracted to A if and only if

$$d(\pi[\psi(a), \psi(b)],\ \pi[\ell(p), \ell(q)]) \geq \delta + e \tag{1}$$

where d represents the process of comparing values in like dimensions, δ is a personal decision threshold, and e is a random disturbance with mean 0 and variance σ^2. The functions $\psi(^*)$ and $\ell(^*)$ transform the objective attribute values into subjective ones. The function $\pi(^*, ^*)$ compares attribute values within a dimension. The comparative process depicted in Equation (1) is very general and restrictions are imposed to the functions $\psi(^*)$, $\ell(^*)$, and $\pi(^*, ^*)$. Furthermore, assuming e to be normally distributed, the propensity of selecting A over B is given by the cumulative normal, $p(A,B)=p(z$ \le $(d-\delta)/\sigma)$.

[1]In the emotion literature, the term ‘‘concerns’’ is used to represent desirable or undesirable ends or well-being states (Frijda, 1994). In the decision-making literature, these end-states are referred to as ‘‘outcomes.’’ Furthermore, in the emotion literature, ‘‘concern strength’’ is used to reference relative degrees of concern importance, whereas in the decision-making literature, this is simply referred to as the importance of outcomes. In order to be consistent with the decision-making literature, this paper will use the ‘‘outcome’’ and ‘‘importance’’ terminology.

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In the current work, we set $\psi(a) = a$, and $\psi(b) = b$, and define

$$\pi^*(a, b) = \frac{|a - b|}{\max\{|a|, |b|\}} \tag{2}$$

The function $\pi^*(a, b)$ produces a value difference relative to the single greatest absolute attribute value. If $a > b > 0$, then Equation (2) produces a difference in the positive evaluations of the two outcomes relative to the greatest positive value. If $0 > a > b$, then Equation (2) produces a difference in the negative evaluations of two outcomes relative to the greatest negative value. Finally, if $a > 0 > b$ then, Equation (2) produces a difference between the positive and negative values, relative to the greater individual absolute deviation from 0. The function thus computes an adjusted attribute difference (i.e., a proportional difference) that represents a measure of advantage (or disadvantage) in terms of a degree of distance between attributes along a negative to positive value continuum.

We define a preference variable d^*, similar to that of PD, but we add importance weights to represent the impact of emotion in choice. For alternatives A and B as previously defined and subjective attribute importance weights β_1 and β_2, the choice for alternative A over alternative B occurs if and only if

$$d^* = \beta_1\{\pi^*(a, b)\} - \beta_2\{\pi^*(p, q)\} > 0 \tag{3}$$

Proportional differences favoring A are added while proportional differences favoring B are subtracted and the preference is determined. The subjective weights β_1 and β_2 measure the degree of emotional impact that each attribute has on the decision maker. We use Fridja's notion that emotions exert a pull/push forces toward alternatives. Under certainty, we assume that these forces are directly linked to the attribute values under consideration and begin by defining β_1 (β_2) as the ratio between the emotional response to an attribute relative to the total emotional response across all attributes being evaluated. This assumption is explicitly tested in Study 1. For decisions dealing with risky options (gambles), we define these weights as ratios of emotional response to entire gambles. We defer discussion of these latter weights to Study 2.

Consider the following hypothetical choice between two jobs as an example of the model's computations. The two jobs, A and B, are described in terms of two attributes, salary and location. The salary for Job A is \$38 000 (i.e., $a = 38\,000$). The salary for Job B is \$30 000 (i.e., $b = 30\,000$). The location of Jobs A and B evoke emotional reactions that can be measured physiologically via skin conductance response (SCR), in microseimen units (μS).[2] The location of Job A evokes an emotional reaction of .21 μS (i.e., $p = .21$). The location of Job B evokes an emotional reaction of .25 μS (i.e., $q = .25$). The salary dimension also produces an emotional reaction with the salary of Job A evoking an emotional reaction of .135 μS, and the salary of Job B evoking an emotional reaction of .115 μS. The SCR measure produces units that represent a physiological measurement of arousal that does not have a positive or a negative valence. We will describe later how we determine whether the emotion is approach or avoidance related. In this example, let us assume that both SCR measures are positive in sign, and thus indicate degrees of positive approach related emotion toward each job location.

Using Equation (2), the proportional difference value of the salary attribute is $|(38\,000 - 30\,000)|/|38\,000| = .21$, favoring A, and the proportional difference value of the location attribute is $|(.21 - .25)|/|.25| = .16$, favoring B. Thus, the proportional difference between the two job options is greater on the salary attribute than on the location attribute. Unless location is weighted more heavily by the decision maker, the choice will favor Job A. In this example and according to the model, the weights are .35 for salary

[2]Emotional reactions can be measured in multiple manners. In this paper, we used a physiological measurement of arousal, SCR, as one proxy for emotional reaction, and a self-reported measure of degree of emotion, the self-assessment manikin (SAM) valence scale (Bradley & Lang, 1994), as another. We defer a fuller discussion of the emotional indices used (i.e., SCR in μS units and the SAM scale) to the methods section.

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($\beta_1 = .25/(135 + .115 + .21 + .25)$), and .65 for location ($\beta_2 = .46/(135 + .115 + .21 + .25)$). Utilizing Equation (3), $d^* = .35(.21) - .65(.16) = -.03$. Therefore, the choice favors Job *B*, dependent in part, on the greater importance of location to the decision maker.

Using this model as a base, we investigate decisions under certainty (Studies 1 and 3) and under risk (Study 2). We present further model specifications in each of the studies.

STUDY 1: DECISIONS UNDER CERTAINTY

In the first study, we asked participants to choose between potential dating partners. Given the median age (19) of our pool of participants, we expected this situation would have a high likelihood of involving an emotional response. In addition, this topic allowed for the presentation of an attribute dimension that is not easily quantified (i.e., physical attractiveness). We used Equation (3) to predict the preference judgments of each participant.

The dating partners varied in terms of physical attractiveness and a quantified intelligence measure. Support for the use of intellect as an important attribute in the choice of dating partners comes from the literature on mate preferences (Kenrick, Sadalla, Groth, & Trost, 1990; Kenrick, Groth, Trost, & Sadalla, 1993). Kenrick et al. (1990) gathered data from both males and females on the minimal acceptable level of intelligence a partner needed when considering that person for a date, sexual relations, a steady date, and for marriage. The data showed that, for women, an increasing level of intelligence was required of their dating partners as the relationship description changed from a date, to sexual relations, to a steady dating partner, to marriage. In addition, women required a date to be at least of average intelligence (Kenrick et al., 1990).

The hypotheses for this study are:

Hypothesis 1: *The emotion aroused in relation to an attribute, relative to the total emotion aroused across all attributes, represents the importance of that attribute to a decision maker. Thus, greater attribute importance is revealed as greater emotional weight.*

Hypothesis 2: *Emotion can serve as an attribute value that is combined with explicitly quantified symbolic information in a proportional difference algorithm to predict preferences, as depicted by Equation (3).*

Hypothesis 3: *Trading emotional and symbolic information via the common currency of proportional differences is more predictive of choice than trading value via the common currency of emotion by itself.*

Hypothesis 4: *The addition of emotionally derived weights to a proportional difference trade-off algorithm improves prediction.*

Slovic et al. (2002) present the case for a common pool of affective tags that can be referenced as a judgment and decision-making heuristic. Furthermore, Peters (2006) has argued that emotion provides a common currency for trading values of dissimilar attributes. We extend the theoretical conceptions advocated by these researchers as well as the HDIF heuristic (Pham, 1998), and the somatic marker (Damasio, 1994) by deriving a simple additive emotional (AE) model at the attribute level which in turn is compared to the predictions we obtain from Equation (3). We believe that the proportional difference combination rule may be superior to AE, because it allows the decision maker to utilize both emotional and explicit symbolic information in a simple trade-off algorithm.

Method

Participants

Forty-seven Ohio University female undergraduate students provided complete and usable data for the study. Students received course credit for their participation.

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Stimulus materials

The decision options were defined by two attributes: intellectual engagement and physical attractiveness. The ''intellectual engagement'' attribute was quantified for the subject with an ''intellectual engagement index.'' This index was described as a person's IQ percentile rank among the US male population. The ranking was said to be highly correlated with the potential dating partner's GPA, SAT/ACT scores, interest in literature, philosophy, culture, science, and intellectual pursuits. In addition, people high on the intellectual engagement scale were described as ''fascinating to listen to'' and ''genuine intellects.'' The ''physical attractiveness'' attribute was manipulated by presenting pictures of potential male dating partners. In a pretest study, 100 participants were asked to rate 60 photos in terms of how attractive each person was in relation to all other collegiate men on a percentile rank scale from 0 to 100 with 0 indicating most unattractive, 50th indicating average attractiveness, and 100th indicating the most attractive college male. Forty photographs ranging in mean percentile ranks from 16.5 to 71.5 were selected from this set of 60 to form 20 unique pairs of dating partners for the present study.

Twenty pairs of potential dates were created with one option pre-rated higher on attractiveness, and the second option rated higher on intellect. The choice pairs were formulated by pairing the pre-rated percentile ranking of the photos with fabricated IQ percentile ranks to establish non-dominated choice pairs across a range of d levels ($-.17$ to $.1$) favoring the higher IQ option.[3] This method was used to establish a base level of proportional differences in the pairs presented for choice; however, it is important to note that the d^* level (Equation (3)) for each pair was expected to differ from person to person because the input in the formulation of the attractiveness attribute is unique to the emotional reaction of each individual. Thus, the average attractiveness ratings served only as an approximate guide in calculating a range of d levels and for creating non-dominated choice pairs (see Table 1).

Experimental design

There was a persuasion and a control condition. In the persuasion condition, participants read a text designed to increase the salience of the IQ attribute. This persuasive description included examples of how people who rate higher on the ''intellect'' scale have a greater earning potential and engender greater satisfaction with the relationship (see Appendix A). The control condition did not include any persuasive text. Participants were randomly assigned to one of the two experimental conditions. The control group had 24 participants. The experimental group had 23 participants. Participants were presented with 20 choices. The between-participant-repeated measures experimental design allowed for a test of whether greater weight was placed on the IQ attribute after persuasion. The 20 choices per subject allowed for modeling of preference judgments within each participant. Additional choices would be desirable for modeling at the individual level; however, because of the lengthy process of this data collection the recording of the physiological measures made additional choice tasks unfeasible.

Procedure

Participants were seated in front of a computer in a reclining chair with a headrest. Physiological recording equipment was attached to each subject's left hand. Following set-up, the experimental procedure began lasting approximately 1 hour.

A computer program presented instructions and choice pairs to the participants. The instructions included practice on how to use the choice scale, the emotion rating scales, and the attribute weighting scale (see

[3]A d level refers to González-Vallejo (2002)'s PD model in which $d = \frac{\max\{|a|,|b|\} - \min\{|a|,|b|\}}{\max\{|a|,|b|\}} - \frac{\max\{|p|,|q|\} - \min\{|p|,|q|\}}{\max\{|p|,|q|\}}$. In this case, a and b are the IQ levels for the options, $a > b$, and p and q are the pre-attractiveness ratings, $q > p$.

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Table 1. Dating choice pairs for Study 1 with initial values and preliminary *d* levels

Pair #	Photo pre-rating	IQ rank	Photo pre-rating	IQ rank	Pre *d*-level
1	50.78	0.92	56.80	0.67	−0.17
2	48.28	0.49	53.03	0.39	−0.11
3	48.80	0.42	53.29	0.34	−0.11
4	57.41	0.76	50.91	0.97	−0.10
5	56.41	0.73	50.58	0.92	−0.10
6	51.07	0.77	58.81	0.59	−0.10
7	52.58	0.36	48.28	0.44	−0.10
8	17.17	0.78	20.12	0.59	−0.10
9	53.17	0.42	48.64	0.46	0.00
10	60.68	0.69	52.33	0.80	0.00
11	20.04	0.70	17.09	0.82	0.00
12	54.38	0.40	49.23	0.44	0.00
13	20.25	0.72	17.91	0.81	0.00
14	52.58	0.92	71.57	0.69	0.02
15	59.33	0.71	51.97	0.73	0.10
16	58.84	0.82	51.75	0.84	0.10
17	19.49	0.87	16.52	0.92	0.10
18	52.06	0.92	60.65	0.88	0.10
19	16.68	0.88	19.59	0.84	0.10
20	51.91	0.62	59.00	0.61	0.10

below). Following the introduction, participants answered four practice questions and then moved into the dating choice section. In the persuasion condition, participants read the persuasive text immediately prior to moving into the dating choice section.

Dating choice pairs were presented one attribute at a time. The physiological emotional reaction to each attribute was recorded during the presentation of each attribute (see below for method). The attribute sequence was counterbalanced and randomized across the 20 pairs with the IQ attribute shown first for half of the pairs and the photograph presented first for the other half. The program was automated during the presentation of the attributes, and each attribute appeared by itself for 12 seconds. Once the attributes had been presented, participants regained control over the pace of the program by clicking ‘‘continue’’ after making their choice, rating each attribute, and assigning the weights to the attribute dimensions.

Physiological measurement of emotional response

The degree of feeling was quantified by measuring the magnitude of the SCR of each participant. SCR is a specific type of measurement of electrodermal activity (EDA). EDA is now commonly used and accepted as a measure of arousal with the amplitude of conductance responses serving as an arousal index (Blascovich & Kelsey, 1990; Venables & Christie, 1980). Theoretically, Ohman, Esteves, Flykt, and Soares, (1993) have proposed that emotion can be defined in a two-dimensional space of approach/avoidance and arousal. The arousal dimension is independent of the approach/avoidance dimension and is aptly captured with EDA recordings (Ohman et al., 1993). In two studies, Detenber, Simons, and Bennett (1998) found that SCR was related to the arousal properties of the image and did not discriminate valence. Thus, while SCR provides an overall indication of degree of arousal, it does not indicate whether the arousal is positive and approach related or negative and avoidance related.

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The self-assessment manikin (SAM) scale (Bradley & Lang, 1994) does provide a measure of direction of emotion. The valence portion of this scale depicts five manikins with varying levels of positive or negative emotion expressed on their faces (i.e., from large smiles to a neither positive nor negative face to large frowns). We developed a continuous version of the SAM scale that allowed for responses in the +4 to −4 range with +4 depicted as a large smile and −4 depicted as a large frown. The sign of this measurement, either positive or negative, was coupled with the SCR in order to capture a direction of the degree of emotional response to attributes during choice.[4]

The SCR measurement was taken from the left hand. Freixa i Baque, Catteau, Miossec, and Roy (1984) conclude that the most recent evidence indicates no lateralization of EDA. SCR was recorded at the skin surface of participants using SCR100c 8mm electrodes with electrode gel and amplified using an EDA100c amplifier by Biopac, Inc. A bipolar placement of the electrodes was used on the medial phalanges of the second and third fingers. The EDA electrode sites were abraded with isopropyl alcohol prep pads prior to electrode placement. A constant voltage procedure passing a 1 Hz signal between the two electrode sites was used to render changes due to dermal response to stimulus presentation. The gain on the EDA100c amplifier was set at 5 μS/V.

Reduction of the electrodermal signal into SCR followed the protocol of previous research that had found a correlation between SCR and SAM scale ratings. Detenber et al. (1998) and Simons, Detenber, Roedema and Reiss (1999) calculated SCR magnitude by visually inspecting each six-second target window for the onset of a SCR and calculating the difference between the peak amplitude and the onset amplitude. Similarly, Tranel and Damasio (1994) calculated affective magnitude by inspecting the latency window of 1–4 seconds after the target stimuli were presented. The amplitude of the largest response that was onset within the window was recorded via inspection of the peak amplitude. Buss, Larsen, Westen, and Semmelroth (1992) visually inspected a 20-second window following emotional imagery for the greatest SCR onset within the window.

For the current study, the 12-second window following the presentation of each attribute was visually inspected for the onset of the SCR. Acknowledge™ software (version 3.8, by Biopac Systems Inc., 2000) rendered a continuous signal of amplitude in microseimens across the 12-second presentation window. A difference measure of the peak amplitude minus the onset amplitude of the largest response onset within the window was calculated. The resulting SCR, in microseimens, indicated the degree of affective arousal while considering each attribute.

Explicit-dependent measures

Self-reported-dependent measures were obtained. After viewing the attributes of each dating partner, participants made choices by moving a sliding ruler on the screen toward either option *A* or *B*. Strength of preference rating elicited the degree to which participants preferred one option over the other. Zero indicated indecision and 100 indicated strongest preference in the designated direction.

After indicating their choice, participants used the SAM scale to rate each attribute of each person on valence. Participants were asked to rate the attributes ''according to how they had felt while they considered each attribute.'' The sign of this measurement was attached to the SCR degree.

Once the explicit emotion ratings from the SAM scale were made, the participants were asked to assign weights, from 0 to 100 points, to the attributes according to how important each comparison dimension was in their choice determination. Moving the ruler on the scale in the direction of greater weight for one of the attributes automatically reduced the same proportion of weight on the second attribute. Thus, the weights

[4]For this decision situation, we assume that negative valence is avoidance related and positive valence is approach related in direction, although we acknowledge this is not always the case as in the case of anger which is negative in valence but is approach related (Lerner & Keltner, 2000).

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Table 2. Correlation matrix of mean (across participants in each condition) responses to stimuli ($n = 40$) Study 1

	Photo pre−rank	SCR_{photo}	SAM_{photo}	IQ rank	SCR_{IQ}	SAM_{IQ}
			Control			
Photo pre-rank	—	0.52**	0.62**	−0.29	−0.10	−0.16
SCR_{photo}		—	0.85**	−0.41	−0.28	−0.26
SAM_{photo}			—	−0.40	−0.30	−0.27
IQ rank				—	0.68**	0.72**
SCR_{IQ}					—	0.78**
SAM_{IQ}						—
			Persuasion			
Photo pre-rank	—	0.52**	0.62**	−0.27	−0.09	−0.15
SCR_{photo}		—	0.83**	−0.41	−0.29	−0.27
SAM_{photo}			—	−0.38	−0.29	−0.25
IQ rank				—	0.67**	0.73**
SCR_{IQ}					—	0.78**
SAM_{IQ}						—

**$p < .01$.

always summed to 100. After the explicit weight assignment was complete, the program proceeded to the next pair comparison.

Results

As a manipulation check, we first tested how the emotion measures related to one another and to the stimulus values described by objective values. We used each stimulus as the unit of analysis ($n = 40$), and averaged over participants, and then correlated the mean measures of emotion with the stimulus values. The correlation matrices of the measures for each condition (control and persuasion) appear in Table 2. As can be seen in the table, the results show that participants were, on average, responding explicitly and physiologically to the stimuli in the expected manner. The critical positive relationships between the IQ rankings and the SCR and SAM measures were all significant. In addition, the positive relationships between the photo pre-rankings and the SCR measures were all significant. These relationships held in both the control and persuasion conditions.

To test Hypothesis 1, we first established that there was a difference in choice as a function of the between participant manipulation of persuasion. The average proportion of choices for the higher IQ date option was computed for each condition. The average proportion of choices toward the higher IQ partner in the control condition was 12.1 out of 20 possible choices. The average proportion of choices toward the higher IQ partner in the persuasion condition was 15.9. The proportions per person were arcsine transformed[5] and a *t*-test, $t(45) = 5.03$, $p < .01$, indicated that individuals were more likely to choose the dating partner with the higher IQ after reading the persuasive communication on dating. Thus, choice was dependent in part on the priming of the importance of the intellect attribute of a dating partner.

To test whether greater attribute importance would be revealed as greater emotional weight for the attribute, a repeated measures ANOVA[6] was performed on the average weight placed on the IQ attribute computed across all pairs, per participant, with three within-participant unique weight determinants: explicit attribute weight assignment, weights derived from emotion as measured by either SCR or by SAM. The between-participant factor was the persuasion condition (control and persuaded). The emotional weights, β_1 (β_2), were derived by summing the total emotional response to one attribute dimension and dividing by the

[5] $y' = \arcsin \times \sqrt{y}$.
[6] We report the multivariate tests for all repeated measures ANOVAS. Wilk's Lambda was used for all tests.

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total emotional responses across both attribute dimensions. In the control condition, the explicit IQ weight $M = 0.46$, the SAM-computed IQ weight $M = 0.50$, and the SCR-computed $M = 0.52$. In contrast, in the persuasion condition, the explicit IQ weight $M = 0.52$, the SAM-computed IQ weight $M = 0.53$, and the SCR-computed $M = 0.54$. An analysis of these mean weights, across participants and pairs, by condition, revealed a main effect of persuasion condition $F(1, 45) = 5.78$, $p < .05$. There was not an interaction of persuasion condition and weight type $F(1, 45) < 1$. This analysis indicates that individuals placed a greater degree of weight on the IQ attribute, after being persuaded of the importance of intellect in a dating partner.

This provides positive evidence for Hypothesis 1: a proportion of emotion aroused in relation to an attribute, relative to the total emotion aroused across all attributes, represents the importance of that attribute to a decision maker. Furthermore, the between-subject persuasion manipulation suggests that attribute importance fluctuates according to the context, and that a proportion of emotion weight can capture that fluctuating importance. Together the analyses on the choice proportions and the weight assignments indicate that not only were people more likely to choose the option with higher IQ after being persuaded, but they also placed greater weight on the IQ attribute in the persuasion condition as determined both explicitly and as derived from their emotional response.

Model testing

To test Hypotheses 2 and 3, three models were computed and compared. Using Equation (3), we first computed d^* without importance weights, including SCR responses for all the attribute values. We refer to this model as d^*-ENW (d^* with emotional values and no weights). A second no weight model included the IQ ranks for the intelligence attribute instead of the emotional responses to these ranks. This model thus combines emotional responses and symbolic information and we refer to it as d^*-SNW (d^* with symbolic information and no weights). We also computed an additive model of emotions. We simply added the total SCR for an option and subtracted the total SCR for the other option. We refer to this as the AE model.

The models were used to predict the magnitude and direction of the strength of preference responses for each person. Table 3 summarizes the results from the correlation analyses for the control group ($n = 24$), the persuasion group ($n = 23$), and overall ($n = 47$). All simple correlations were positive as expected. The average mean R^2 values and the R^2 quartiles appear in the table.

In order to test whether the models were significant predictors of choice across participants, and also to test for differences between the average correlations of each model, a Fisher's z-transformation[7] was computed for each correlation on each participant. The resulting z-scores served as the dependent variable in the following model comparison tests. We first tested whether the pure emotional models of d^*-ENW and AE were significant predictors of choice. The Fisher's z-transformed correlations of the SCR model differed

Table 3. Mean R^2 for certainty of choice by each model across conditions and overall

	Control		Persuasion		Overall	
Model	R^2	R^2 quartiles	R^2	R^2 quartiles	R^2	R^2 quartiles
1:d^*-ENW	0.18	(0.03, 0.10, 0.34)	0.20	(0.13, 0.21, 0.29)	0.19	(0.05, 0.15, 0.31)
2:AE	0.10	(0.01, 0.05, 0.14)	0.07	(0.01, 0.07, 0.11)	0.10	(0.01, 0.06, 0.13)
3:d^*-SNW	0.23	(0.06, 0.15, 0.40)	0.25	(0.16, 0.23, 0.37)	0.24	(0.08, 0.19, 0.37)
4:d^*	0.16	(0.02, 0.11, 0.28)	0.22	(0.13, 0.20, 0.30)	0.19	(0.04, 0.18, 0.28)

[7] $z = (.5)\log_e(|(1 + r)/(1 - r)|)$.

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significantly from 0 as indicated by a one-sample t-test t (46) = 10.25, $p < .01$. The AE model transformed correlations also differed significantly from 0 t (46) = 6.09, $p < .01$. These results support the conclusion that emotion, as measured by SCR, can be appropriately modeled with a proportional difference choice algorithm.

As can be seen in Table 3, the average R^2 value for the AE model is lower than the average R^2 value for the d^*-ENW model which is in turn lower than the average R^2 value for the d^*-SNW model. Two simple comparisons of the Fisher's z-transformed correlations of these models allow us to test Hypotheses 2 and 3. A direct comparison of the AE model with d^*-ENW, revealed that d^*-ENW model is superior in its prediction of choice, dependent t (46) = 5.62, $p < .01$. Furthermore, a direct comparison revealed that the d^*-SNW model outperformed the d^*-ENW model t (46) = 3.05, $p < .01$. These findings are particularly interesting, in that they represent positive evidence for a mixed cognitive-emotional model, in support of Hypothesis 2. Given that the d^*-SNW model outperformed the d^*-ENW model which in turn outperformed the AE model, these results also support Hypothesis 3. Trading emotional and symbolic information via the common currency of proportional differences is more predictive of preferences than trading values represented by the common currency of emotion itself, in this situation.

Finally, we computed a full model utilizing Equation (3), in order to test Hypothesis 4 that the addition of emotionally derived weights to the proportional difference trade-off algorithm improves prediction. The full d^* model is identical to the d^*-SNW, with the addition of emotionally derived weights from SCR. As seen in Table 3, the full model does not outperform the d^*-SNW model. This finding was contrary to our expectations.

Discussion: Study 1

A major aim of the first study was to specify a manner by which emotional information combines with symbolic information to produce preferences. The theoretical basis of our predictions rested on the notion that emotion evoked during decisions may serve as information to the decision maker on the value of attributes that are not explicitly quantified. In addition, we hypothesized that emotions function as a push or pull weighting mechanism. The results of this first study provided evidence that (a) the emotion aroused in relation to an attribute, relative to the total emotion aroused across all attributes, represents the importance of that attribute to a decision maker, (b) emotion can serve as an attribute value that combines with explicitly quantified symbolic information in a proportional difference algorithm, (c) preference predictions made with trade-offs via the common currency of proportional differences are superior to preference predictions made with a simple additive model of emotion. Finally, Study 1 did not provide evidence for the notion that adding emotionally derived weights to the basic proportional difference algorithm improves choice prediction.

The results from Study 1 are interesting from numerous perspectives. These results represent, to the best of our knowledge, the first demonstration of how a physiological measurement of arousal can be combined mathematically with cognitively manipulated symbolic information, in a decision equation to successfully predict preferences. In addition, these results suggest that the quantitative role of emotion in choice is more complex than simple valence flag theories have previously suggested. We believe that the current work is a substantial advancement because it demonstrates a specific manner by which emotion can be incorporated quantitatively into preference formation, beyond a simple "winner-takes-all" approach of purely emotional models. Namely, the results suggest that the degree and direction of anticipatory emotion can serve as an attribute value that is usefully traded with dissimilarly scaled symbolic information via a proportional difference algorithm. That is, emotion can be a tradable quantity in choice.

The results on our hypothesis of how emotion can serve as an attribute importance weight were not definitive. In terms of importance weights, the results support our contention that the proportion of emotion aroused for an attribute, relative to the total emotion aroused across all attributes, serves as an indication of the importance of that attribute. However, the model that utilized emotional reactions as attribute values and

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emotional weights did not outperform a similar model which did not utilize these emotional weights. Study 2 was designed to isolate the role of emotional weights to further explore this issue. In addition, Study 2 explores the role of emotion in decision-making under risk, and expands the current model specification to account for decisions within this domain.

STUDY 2: DECISION-MAKING UNDER RISK

Decision-making under risk describes decisions where the outcome of at least one choice alternative occurs with some known probability. Early models of decisions under risk include the expected value (EV) model, which combines outcome values with their probability multiplicatively to produce an EV for each prospect considered in choice. The origins of expected utility (EU) theory, a variation on EV, trace back to Bernoulli (1738; as cited by Mellers, 2000). SEU was introduced by Savage (1954), who incorporated into EU theory the notion that probabilities are subjective beliefs. A vast literature has demonstrated violations of both deterministic and stochastic axioms of SEU (Schoemaker, 1982). Many alternative models have been proposed and tested, including weighted EU (Chew & Waller, 1986), rank-dependent EU (Luce, 1990; Quiggin, 1982, 1985), as well as nonlinear weighting theories, including cumulative prospect theory (Tversky & Kahneman, 1992), and configural weighting models (Weber, 1994). Camerer (1992) provides a review of these models and finds that nonlinear weighting models, such as prospect theory, perform the best descriptively.

Prospect theory hypothesizes that prospects for choice are coded as either gains or losses, relative to a reference point, and probabilities are transformed into decision weights. However, recent research is showing that there are important individual differences that might play a role in determining the extent to which people switch from being risk averse in gains to risk seeking in losses (González-Vallejo et al., 2003; Schneider & Lopes, 1986; Zickar & Highhouse, 1998). These studies, nevertheless, do not fully specify the mechanisms driving these risk sensitivity differences. This is consistent with the recent call for research investigating motivational and emotional factors in risky choice (Kuhberger, 1998).

In Study 2, we followed the same modeling strategy as Study 1 to predict strength of preference, but we limited the role of the symbolic information. Utilizing González-Vallejo's (2002) d variable, we constructed stimuli choice pairs in which both options had equal EVs and thus $d = 0$ in all instances. Thus, both PD and EV make no systematic predictions on choice preferences based on the stimuli alone. While this approach restricts the level of variability that could be explained in behavior as a function of d values, it allows for isolating the role of emotion, keeping everything else constant. More specifically, in Study 2 we looked for changes in emotional responses that corresponded with changes in risk attitudes when evaluating options offering gains versus those offering losses.

The structure of the stimuli of Study 2 also allows for a test of how well an emotional trade-off model can account for common ratio effects in decisions under risk. A violation of the *common ratio* property of SEU is illustrated in the following example from Camerer (1992). Let $A =$ a 100% chance of 1 million and $B =$ an 80% chance of 5 million. Assume the decision maker prefers A to B. Next, assume each alternative's probability is multiplied by the common ratio of (.05) to derive: $A' =$ a 5% chance of 1 million and $B' =$ a 4% chance of 5 million. A reversal of preference from A preferred to B, to B' preferred to A' is an example of a common ratio effect.

Tversky and Kahneman (1981) used prospect theory to explain common ratio effects between gambles with certain versus uncertain outcomes. Our emotional approach differs in that we expect to demonstrate the large role that emotion plays when individuals contemplate choices that involve probabilities. Equations (4) and (5) specify a possible emotional/symbolic combination that can deal with common ratio effects at all levels of the probability continuum.

DOI: 10.1002/bdm

Emotional weights in decisions under risk

We begin with Equation (3) and specify decision weights, β_1 and β_2, as the relative emotional reactions to risky prospects of the form (a, p) where a is an amount to be obtained with probability p. We suggest that while probabilities can affect the emotional reaction to an outcome, emotional reactions are not to the individual probabilities per se. Rather, decision makers are assumed to be emotionally responding to *options* in their entirety. In doing so, probabilities can heighten or dampen the emotional reaction to an outcome (Rottenstreich & Hsee, 2001).

The emotion weights, β_1 and β_2, are derived from emotional reactions to options (i.e., outcomes and their probabilities) following a proportional difference algorithm as in Study 1. Let $e(A)$ be the emotional reaction to option A, and $e(B)$ be the emotional reaction to option B, then

$$\beta_1 = .5 + \frac{e(A) - e(B)}{\text{sum}\{|e(A)|, |e(B)|\}}[.5], \text{ and} \tag{4}$$

$$\beta_2 = 1 - \beta_1 \tag{5}$$

Equations (4) and (5) produce emotion importance weights that depend on the difference of the emotions for the two options relative to the total emotion felt. The emotional weights are applied to the advantages of options A and B, respectively, indicating a degree to which the decision maker weighs the advantages inherent in one option more than the advantages inherent in a second option. Intuitively, one can interpret the calculation of β_i as the relative degree to which the emotional reaction pushes or pulls the decision maker toward option A or B. This aspect of the weighting scheme is important from the perspective of the function of emotion as a director of approach versus avoidance action (Cosmides & Tooby, 2000). If a positive emotion indicates that an individual desires to move toward an option and a negative emotion indicates that an individual desires to move away from the alternative option, then no trade-off calculations between the options are needed. The pull of the emotion toward the positive option and the push of the negative emotion away from the negative option produce a choice for the positive option. Equations (4) and (5) capture this quality of the function of emotion. Finally, scaling units of .5 are added and multiplied to keep the weights within 0 and 1 as demonstrated in the example below.

Assume that a decision maker is investing \$1000 and is choosing between two stocks with the following appreciation estimates and a broker's best estimate of the probability of that appreciation: Stock A (\$10 000, .3) and Stock B (\$6000, .5). Also assume that the emotional response to both options is positive. Let the emotional reaction to stock A $e(A) = .35$, and let the emotional reaction to Stock B $e(B) = .25$, inserting these values into Equations (4) and (5) produce

$$\beta_1 = .5 + \frac{.35 - .25}{\text{sum}\{|.35|, |.25|\}}[.5] = .5 + \frac{.1}{.6}[.5] = .5 + .08 = .58$$

$$\beta_2 = .1 - .58 = .42$$

Inserting these weights into Equation (3) produces a preference for option A:

$$d^* = \left\{\beta_1\left[\frac{a-b}{\max\{|a|, |b|\}}\right]\right\} - \left\{\beta_2\left[\frac{p-q}{\max\{|p|, q|\}}\right]\right\} = \left\{.58\left[\frac{|10\,000 - 6000|}{10.000}\right]\right\} - \left\{.42\left[\frac{|.5 - .3|}{.5}\right]\right\}$$
$$= .58(.4) - .41(.4) = .23 - .17 = .06$$

The present study created a gamble pair structure such that d^* from Equation (3) depends only on the emotional weight β_1. In this manner, we test a strong assumption that the emotional weights computed via Equation (4) are predictive of the evaluation judgments. As in the first study, we compared these predictions

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to that of a simpler additive model (AE) in which the difference in emotional reaction moves the decision maker toward the more positive option. Specific hypotheses are:

Hypothesis 5: *Emotionally derived weights correlate positively with the preference judgments both in gains and loss situations, when everything else is kept constant.*

Hypothesis 6: *A proportion of emotion model will outperform a simple additive emotion model.*

Hypothesis 7: *An emotional trade-off between gambles predicts common ratio effects.*

Method

Participants

A total of 54 Ohio University undergraduate students participated for introductory psychology course credit.

Stimuli and design

Participants were asked to make choices between 42 pairs of gambles. The gamble pairs appear in Appendix B. Half of the gambles were in a gain context and half of the gambles were in a loss context. The gamble pairs for losses equal the gamble pairs in gains multiplied by -1. The pairs were created from a PD perspective with a single *d*-level of 0. In addition, one-third of the pairs have low probabilities (.08 and .10), another third have moderate probabilities (.4 and .5), and the last third have high probabilities including a certain option (.8 and 1). This design produces a probability level factor with three levels (low, moderate, and high), and the pairs at each level represent some ratio of the pairs at every other level. Note also in Appendix B that there is an outcome factor with seven levels. Each outcome pair is repeated across each probability level.

The order of gain and loss choices was counterbalanced between participants. Half of the participants made 21 choices in gains first, and half of the participants made choices in losses first. Individuals in the gains first condition started with 0 dollars. After 21 choices in gains, these participants were told that they won \$50 and were actually given \$50 by the experimenter. They were told that they could lose this money in the second half of the experiment. These participants then made 21 choices in losses and after they were finished they were told that they had lost all of the money. Participants were then debriefed and given \$5 (to their surprise) plus two experimental credits for their participation.

Participants in the losses first condition were given \$50 at the beginning of the experiment and were asked to make choices among losing gambles in which they could lose the \$50. After making 21 choices in losses, participants were told that they had lost all of the \$50 and would be starting at 0 for the gains condition. After making 21 choices in gains, participants were told that they did not win any money. Participants were then debriefed and given \$5 (to their surprise) plus two experimental credits for their participation.

Procedure

Participants read instructional information on how the subsequent gamble choices would proceed and practiced using the preference scale and the importance weight scale (described below). Individuals were told that they would be making choices between gambles involving actual money. They were told that six of the gambles they chose would be randomly selected and played for actual money. The outcomes of those gambles were predetermined, but the participants were unaware of this until debriefing at the end of the experiment.

In order to engage participants in the experiment, and heighten their emotional reaction to the choices, participants were shown how the gambles were to be played with actual dollar bills. Six bags containing red and white poker chips were presented to the participants. Each bag contained 100 chips and represented one of the six probability levels associated with the potential outcomes in the experiment (.08, .1, .4, .5, .8, 1),

DOI: 10.1002/bdm

with the number of red chips representing the probability level. For example, the .08 probability bag contained 8 red chips and 92 white chips. The experimenter demonstrated how a selected gamble would be played for the participant. The participant was told that the computer would randomly choose three of the gambles selected by the participant in each condition and then the experimenter would play those gambles for the participant.

Next, participants had the physiological equipment attached to their non-dominant hand. The experimenter gave instructions on how the choices would proceed on the screen. Once a stable baseline level of arousal was obtained, the presentation of the gambles began. Participants made choices between 21 gamble pairs in gains and 21 pairs in losses. The gamble pairs were presented with a payout (or penalty) and a probability for each gamble. SCR was recorded in the 5-second window following the presentation of each gamble.

Physiological measurement of emotion

Each gamble of a pair appeared on the computer with pictures of the dollar amounts and the associated probability of the outcomes next to the pictures. Each alternative initially appeared by itself, and an SCR was recorded during the 5-second window directly following its appearance on the screen. SCR was recorded at the skin surface of the non-dominant hand of participants using the same procedure as Study 1.

Reduction of the electrodermal signal into SCR followed the procedure detailed in Study 1. The 5-second window following the presentation of each gamble was visually inspected for the onset of an SCR. A difference measure of the peak amplitude minus the onset amplitude of the largest response onset within the window was calculated. The resulting SCR, in microseimens, indicated the degree of arousal while considering each gamble. The direction of the SCR as positive approach or negative avoidance was indicated by the participant's use of the SAM scale. Participants rated their emotion after each gamble was presented and before making choices.

Self-reported measurement of emotion

As in Study 1, participants used the SAM scale, moving a cursor along the continuous scale to indicate the direction and degree of their experienced positive approach or negative avoidance emotion they felt toward each gamble.

Strength of preference

Participants provided a strength of preference judgment by utilizing the same scale as Study 1. This was the last judgment made in the series of measures.

Results

Each participant provided emotional responses for 21 pairs in gains and 21 pairs in losses. We computed the weight β_1 using Equation (4) and the SCR measures. We proceeded to test Hypothesis 5 by relating the emotionally derived weights to the preference judgments. Each participant had 42 d^* calculations overall, 21 in gains and 21 in losses.

The Fisher's z-transformed correlation of the strength of preference judgments and the weights showed that the mean was significantly different from 0, $t\ (53) = 1.96\ p < .05$, (mean $R^2 = 0.02$). This provides evidence that incorporating physiologically measured emotional weights into a decision-making model improves prediction, when the gambles do not differ in expected payoffs.

As in the first study, we further investigated the relations between the emotional responses and the preference judgments. The possibility that preferences relate to the simple difference of the emotional responses to the options is captured by the AE model. We calculated these differences using SCR and correlated those differences with the strength of preference judgments for each participant. The mean R^2 for the SCR difference was equal to .02. The individual correlations were Fisher's z-transformed and the resulting variable was a significant predictor of preference $t\ (53) = 1.90$, $p < .05$, one-tail when tested against

DOI: 10.1002/bdm

a null value of 0. To test Hypothesis 6, we compared the AE and d^* models. The AE model did not differ significantly from the d^* model $t\ (52) = .20$, $p > .05$.

Next, we tested Hypothesis 7 that emotional trade-off models can account for the common ratio effect. The probabilities of the first third of the pairs represent the probabilities of the final third multiplied by the common ratio of .1 (see Appendix B). The probabilities of the second third of the pairs represent the probabilities of the final third multiplied by the common ratio of .5. To conduct the analysis, first the number of instances in which an individual showed a reversal of preference between pairs that shared a common ratio was counted. There were 14 possible instances of this in gains, and 14 possible instances of this in losses, per participant. Next, the number of times that a preference reversal occurred, and was predicted to occur by the emotional model, was counted. A correctly predicted reversal was indicated by the emotional model successfully predicting the preference at one probability level and then successfully predicting the reversal of preference at the second probability level.

In this circumstance, because a direction of preference reversal is being counted and not a strength of preference, and because the experimental design restrictions on the symbolic information (i.e., $d = 0$), the AE model and the d^* model make the same direction of choice predictions.

The average proportion of correct predictions expected by chance is .25 because the probability of correctly predicting the direction of choice across two choices by chance is $.5 \times .5 = .25$. Averaging the proportion of correct predictions across individuals, these emotional trade-off models accounted for 30% of violations on average. The proportion of correct violation predictions per participant ranged from a minimum of .04 to a maximum of .6. To test whether the model predictions were better than chance, the proportions of correctly predicted preference reversals for the emotion-based models per individual were arcsine transformed and the mean of the transformed proportions were tested against a null value of 1.05, which is the transformed value of the proportion of correct predictions expected by chance (i.e., .25). The emotion models were better than chance predictions, $t\ (53) = 1.67$, $p < .05$, one-tail.

Discussion: Study 2

The second study was created to further test the notion that emotionally derived importance weights are predictive of preferences and to test the proportion of emotion model within the domain of decision-making under risk. A relative weighting approach, in which the positive emotional reaction to one alternative was compared to that of the other alternative (the difference taken relative to the total emotion felt in the decision), showed that emotional weights were predictive of preferences. This is consistent with the findings of Study 1 that a proportion of emotion is related to the importance judgments of a decision maker and in addition it provides evidence that adding emotionally based importance weights to the basic proportional difference algorithm improves choice prediction.

The stimuli for study 2 were very restrictive, in the sense that all EV differences of the choice pairs were set to equal 0, and the d-levels were also set to 0. This restrictive environment allowed for greater isolation of emotional effects; however, it may also have reduced our ability to parse differences between the d^* model and the AE model. In study 2, both of these models were predictive of preferences, but they were not significantly different from one another. This indicates that the current stimuli do not differentiate between the models well in terms of isolating the unique predictions of each type of model. In particular, the fact that all gamble pairs reside at a d level of .0 limits the tests of the d^* model to situations where unique symbolic information cannot have an effect on preferences. In Study 1, where the unique symbolic information could have an effect on preferences, the mixed cognitive-emotional model of d^* significantly outperformed the AE model.

The emotional trade-off models in Study 2 were also found to be predictive of preference reversals across pairs of gambles that share common ratios of probabilities. The emotional trade-off models predicted 30% of preference reversals on average, indicating that emotion may play a key role in these types of violations of EU theory (e.g., Allais, 1953).

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Post-hoc analyses (Studies 1 and 2)

The results from Study 2 showing that preference judgments for risky alternatives are related to online emotional judgments is consistent with the risk-as-feelings hypothesis (Loewenstein, Weber, Hsee, & Welch, 2001). We hypothesized that a physiological measure, SCR, would capture the anticipatory emotion construct from this theory, and indeed these measures are related to preferences in decisions under risk (Study 2), as well as under certainty (Study 1).

Given that the SAM valence measures provide both a direction and degree of emotion, it is possible to use the SAM values as predictors of preference. Therefore, in a post-hoc analysis, we created d^* models for Studies 1 and 2 using the SAM valence measures and we found that these models were indeed significantly related to preferences (Study 1 d^* model average $R^2 = .53$; Study 2 d^* model average $R^2 = .11$). This finding is consistent with Schwarz and Clore's (1983) notion that effect is information that a decision maker can consciously use (also see Pham, 1998). These findings are interesting and the heightened levels of preference prediction, as indicated by the much higher R^2 values, raise the intriguing question of whether decision makers use of the SAM scale represents a reflective cognitive system that has processed the physiological response and interpreted that response for use in a decision-making algorithm.

It is important to note that the SAM model analyses were post-hoc, and there are at least a couple of factors that hinder our ability to interpret the findings clearly. First, the SAM valence measures in Study 1 were obtained after preference judgments were made, so it is possible that these evaluations could reflect justification by the decision maker of their stated preferences. This was not an issue in Study 2, because we obtained the SAM valence responses before the preference judgment was made; however, prediction levels dropped substantially in Study 2. Second, the SAM d^* models were computed using the valence scale of the SAM. The SAM valence scale was included in Studies 1 and 2 as a way to attach a positive or negative sign to the SCR measure of arousal. The degree of movement on the scale was used as a proxy measurement of magnitude of emotion. However, the SAM also includes an arousal dimension in addition to the valence dimension.[8] The arousal measurement scale depicts manikins with increasing levels of arousal appearing inside the body. The SAM arousal dimension has been shown to be more strongly related to physiological measures of emotional arousal, including SCR, than the SAM valence dimension (Detenber et al., 1998; Simons et al., 1999). Thus, the post-hoc analyses of Studies 1 and 2 may not be the best representation of a self-reported correlate of the physiological measures of emotion. We address these issues in the design of Study 3.

Study 3 provides a platform for testing the SAM arousal scale as a predictor of preference in an a priori design. In Study 3, we used the SAM arousal scale as the self-reported measure of degree of emotional arousal and we used the SAM valence scale to indicate the sign of the self-reported and physiologically measured arousal.

STUDY 3

In Study 3, we seek to provide additional evidence that combining SCR with symbolic cognitive information improves choice predictions. In addition, we seek to test the purely AE model against a proportion of emotion in a situation more amenable to cognitive symbolic trade-offs. Participants made decisions between diamond rings that varied according to carat size and price and both attributes were defined through quantitative symbolic information. This allows for fair tests of models that include only symbolic information with models that include the interaction of symbolic and emotional information. Emotional reactions to both

[8]The SAM also includes a dominance dimension. However, the dominance scale was not used in the current research because it has been shown across many studies to be highly redundant with the valence scale ($r > .85$) (Detenber et al., 1998).

DOI: 10.1002/bdm

quantitative attributes were recorded using SCR. Finally, we sought to investigate the relationship between self-report measures of emotion and preference more deliberately than in Studies 1 and 2 by using an a priori design that incorporates the SAM arousal scale as a self-reported measure of the degree of arousal, and the SAM valence scale as a way to attach a positive or negative sign to the self-reported and physiological measures of arousal.

Specific hypotheses for Study 3 are:

Hypothesis 8: *A proportion of emotion model will outperform a simple additive emotion model.*

This hypothesis is the same as Hypotheses 3 and 6. Given the positive evidence for Hypothesis 3 from Study 1, and the lack of evidence for Hypothesis 6 from Study 2 we sought to test this hypothesis in an environment where the cognitive symbolic information was not as restricted as it was in Study 2. If the reasoning behind the lack of evidence for Hypothesis 6 in Study 2 is accurate, a less restrictive symbolic environment should allow for any advantages of the proportion of emotion model to be revealed. The hypothesis is tested with both the SCR measures and the SAM arousal measures of emotion.

Hypothesis 9: *Adding SCR to a model including only symbolic information will improve preference prediction.*

In testing this hypothesis, we add the raw SCR measures into a regression equation already containing the symbolic information inherent in the stimuli to test the additional predictive validity of the SCR measures without specifying process.

Method

Participants

A total of 20 Ohio University female undergraduate students participated for introductory psychology course credit. Three participants were removed from the study due to negligible emotional responses (SCR, $M < 0.005\ \mu S$), leaving a final sample of 17 participants. Analyses were again completed at the individual level, providing 17 independent tests of the emotional models.

Stimuli and design

Participants were asked to make 40 choices between pairs of diamonds. Pairs of diamonds were created using a range of prices and carat sizes from bluenile.com® such that a trade-off between carat size and cost was necessary. A pilot study of 43 female participants revealed an average decision threshold for trade-offs between carat size and price of $d = -.06$ for this participant population. Therefore, we created pairs of diamonds at two d levels: $-.2$ and .0 to ensure the stimuli were within a range of d levels that would likely require difficult trade-offs between price and carat size. We created four pairs of diamonds at the two d levels (see Table 4). Participants made 10 choices between each of the pairs. The order of the diamonds within each pair was randomized such that the diamond with the larger carat size in each pair randomly appeared as either the first or second diamond shown in a pair.

Procedure

Participants read instructional information on how the pairs would proceed and practiced using the measurement scales. Next, participants had the physiological equipment attached to their non-dominant hand. A stable baseline level of arousal was obtained and then the procession of diamond pairs began. Each diamond in a pair was presented with a carat size and a price. SCR was recorded in the 6-second window

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Table 4. Study 3 stimuli

		Diamond *A*		Diamond *B*	
Pair #	*d* level	Carat size	Price	Carat size	Price
1	−0.20	0.95	\$9300	0.73	\$5250
2	0.00	1.21	\$12 500	1.01	\$10 375
3	−0.20	1.40	\$17 410	1.14	\$10 780
4	0.00	0.71	\$4650	0.58	\$3780

following the presentation of each attribute of each diamond in a pair. Following the presentation of each diamond, the respondent was asked to specify the degree of her emotional reaction to each attribute of each diamond using the SAM arousal scale and the direction of that emotional reaction using the SAM valence scale. Finally, each participant indicated her choice of diamond using the strength of preference scale.

Physiological measurement of emotion

A picture of the diamond with the carat size printed underneath it appeared on the computer screen, and separately the price of the diamond appeared on the screen. Each attribute of each alternative appeared by itself, and an SCR was recorded during the 6-second window directly following its appearance on the screen. SCR was recorded using the same procedure as Studies 1 and 2. Reduction of the electrodermal signal into SCR also followed the same procedure as Studies 1 and 2.

Self-reported measurement of emotion

As in Studies 1 and 2, participants used the SAM valence scale to indicate the direction of their experienced positive approach or negative avoidance emotion they felt toward the carat size and price of each diamond. In addition, participants used the SAM arousal scale to indicate the magnitude of emotional arousal they felt toward the carat size and price of each diamond. The SAM arousal scale was a continuous scale ranging from 1 to 9.

Strength of preference

Participants provided strength of preference judgments by utilizing the same scale as Studies 1 and 2. This was the last judgment made in the series of measures.

Results

First, we test Hypothesis 8 using the SCR and the SAM arousal measures separately. The two emotional mechanisms tested are the d^* model and the AE model from Studies 1 and 2. The d^* model is based on Equation (3) in which the emotionally derived importance weights in the equation interact with the symbolic information to produce a preference prediction. The AE model is a simple AE model. The models were first compared using SCR inputs and then using SAM arousal inputs.

The average correlation of the d^* SCR model and preference ($r = .201$) was significantly different from 0 $t\ (16) = 5.55$, $p < .05$ and the average correlation of the AE SCR model and preference ($r = .166$) was also significantly different from 0 $t\ (16) = 3.93$, $p < .05$. The mean difference between the two models was in the predicted direction but did not reach significance $t\ (16) = .64$, $p > .05$.

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Table 5. Correlations of AE and d^* models using SAM arousal measures as inputs

	AE SAM		d^* SAM	
Participant	$r(39)$	p	$r(39)$	p
1	0.497	0.001	0.641	0.000
2	0.264	0.099	0.451	0.004
3	0.426	0.006	0.623	0.000
4	0.229	0.156	−0.023	0.887
5	−0.052	0.752	0.342	0.031
6	0.626	0.000	0.585	0.000
7	0.049	0.765	0.093	0.568
8	0.484	0.002	0.617	0.000
9	0.391	0.013	0.444	0.004
10	0.223	0.166	0.457	0.003
11	0.471	0.002	0.851	0.000
12	0.175	0.281	0.439	0.005
13	0.296	0.063	0.668	0.000
14	0.034	0.835	0.522	0.001
15	0.225	0.163	0.475	0.002
16	0.534	0.000	0.218	0.177
17	0.258	0.108	0.465	0.002
Average r	0.302		0.463	

However, testing the specified SAM arousal models did provide definitive evidence of the predictive advantage of the d^* model over the AE model. The d^* model accounted for more variance in preferences than the AE model. The d^* models' average $R^2 = .26$ compared to the AE models' average $R^2 = .13$. A paired sample t-test on the Fisher's z-transformed correlations of each model across individuals, showed a significant difference between the d^* model and the AE model $t\,(16) = 3.07$, $p < .05$. The model correlations with strength of preference for each participant appear in Table 5. Furthermore, the d^* model was a better predictor than AE in 14 out of 17 cases (82.3%) (binomial test of proportion, $p < .05$).

Next to test Hypothesis 9, each participant's strength of preference was predicted using a regression procedure where the d-levels from the PD model were entered in an equation as the representation of the symbolic information as a basic symbolic model. Then a second model was calculated which added the SCR to each attribute into the predictive equation (four variables per strength of preference judgment) along with the base symbolic information. Thus, six parameters were estimated in the symbolic plus SCR model, plus the regression intercept, for each individual's model across 40 choice pairs leaving 33 degrees of freedom for significance testing. Comparing these models tests the ability of SCR measures to predict choices above and beyond basic cognitive symbolic information.

As expected, the symbolic information model was predictive of strength of preference, accounting for an average of 35% of the variance across individuals. The symbolic plus SCR model produced equations that accounted for 47% of the variance on average. A paired sample t-test on the Fisher's z-transformed correlations of each model across individuals showed a significant difference between the symbolic and the symbolic plus SCR model $t\,(16) = 5.2$, $p < .05$. In fact, the SCR measures increased the R^2 values in 17 out of 17 cases (see Table 6). The probability of this pattern occurring by chance is $p < .05$.

These data support Hypothesis 9. We gain explanatory power by adding SCR to symbolic information to predict preferences. This suggests that physiological measures of emotion can be effectively combined with

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Table 6. Study 3 R^2 values for seven-parameter regression equations predicting individual preference with symbolic information, SCR and SAM measures

Participant	Symbolic information	Symbolic information + SCR	Symbolic information + SAM
1	0.794	0.807	0.826
2	0.205	0.275	0.484
3	0.004	0.033	0.057
4	0.103	0.446	0.836
5	0.207	0.210	0.420
6	0.750	0.755	0.774
7	0.039	0.147	0.349
8	0.349	0.633	0.754
9	0.327	0.425	0.647
10	0.500	0.597	0.565
11	0.929	0.937	0.947
12	0.290	0.467	0.598
13	0.481	0.630	0.512
14	0.036	0.104	0.182
15	0.287	0.390	0.595
16	0.443	0.650	0.721
17	0.278	0.416	0.606
Average R^2	0.354	0.466	0.581

the symbolic information of a stimulus in decision-making models and that the structure of the models need not be restricted to the AE or d^* forms.

Finally, the same regression procedure was used to predict participant's preferences using the SAM arousal values as the emotion inputs. A symbolic plus SAM model produced individual model equations that accounted for 58% of the variance on average. Paired sample t-tests on the Fisher's z-transformed correlations of the models across individuals showed the symbolic plus SAM model outperformed the symbolic only model $t\ (16) = 5.3$, $p < .05$, as well as the symbolic plus SCR model $t\ (16) = 5.3$, $p < .05$.

Discussion: Study 3

The third study was designed to test the emotional models in a decision environment that would allow for model differentiation, and test the hypothesis of emotion's role as a decision mechanism at work beneath the model parameters estimated in PD. Study 3 provides additional evidence that (a) adding physiological measures of arousal to symbolic information improves choice predictions and (b) on average, the proportion of emotion model is a better predictor of preferences than a simple AE model. These findings continue to suggest that emotion is a tradeable quantity.

The results of the SCR analyses provide additional insight on the level of prediction accuracy of the structurally specified AE and d^* models. As expected, the freely estimated seven parameter SCR regression approach accounted for more variance in preference than either the AE or d^* SCR approaches. We would expect a model with seven freely estimated parameters to outperform fully specified models that do not estimate any parameters unless the AE or d^* models were assumed to be perfectly capturing the manner by which emotion influences choice. A freely estimated model with seven parameters has greater agility. Nonetheless, the free estimation model exercise is interesting in at least a couple of ways. First, we learn that incorporating raw SCR data into a decision equation improves choice prediction. Second, the fact that the freely estimated regression model is a better predictor of preference, indicates that neither the AE model nor

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the d^* model has the entire story correct. This finding is particularly useful as future research seeks to further specify theoretically based process models, such as AE and the d^* model, in attempts to understand the nature of decision-making mechanisms.

Study 3 also explored the predictive validity of self-reported emotional measures more deliberately. The SAM arousal measures proved to be better predictors of preferences than the SCR measures. The data from Study 3 provides the most definitive evidence of the superiority of the self-reported emotion measures across all three studies, because (a) the measures were taken before choices were made and (b) the analyses were not post-hoc. The design of the study used the SAM arousal measure which has been shown to be related to physiological measures of arousal as compared the SAM valence scale.

There are multiple potential explanations for the predictive superiority of the self-report measures of emotion versus the physiological measures. First, the self-report measures may be less noisy than the physiological measures. Second, it is possible that the self-report and physiological measures are not capturing the same construct. Specifically, it has been hypothesized that self-report measures of emotion may represent an individual's reflection and interpretation of their physiological response (Detenber et al., 1998; Lang, 1993). This reflection and interpretation may influence the manner in which the emotional information coming from the physiological system is being incorporated into an individual's decision algorithm. Future research should attempt to tease out which of these potential explanations is more appropriate.

GENERAL DISCUSSION

The goal of the current research was to advance and test quantitative models of the way in which anticipatory emotion and symbolic information combine to produce preference judgments. We examined decisions under certainty and under risk in order to test the generality of the theoretically proposed hypotheses. In particular, we hypothesized that when cognitively based trade-offs must be made, decision makers use explicitly quantified symbolic and emotional information as values in the combination rule proposed by González-Vallejo (2002). Furthermore, we proposed that emotional information would serve as a weighting mechanism that could move the decision maker toward or away from an option. The definition of these weights followed a proportional rule defined at the level of the attribute, in decisions under certainty (Studies 1 and 3), and at the level of options for decisions under risk (Study 2).

Study 1 showed that emotional responses (measured physiologically and with explicit ratings) combined with the symbolic information describing the options were more predictive of strength of preference judgments than a basic AE rule. The AE model enjoys the theoretical value of parsimony of process. Simply adding the benefits and subtracting the detractions seems psychologically easy to do. In fact, this simple model corresponds to some degree with the HDIF heuristic (Pham, 1998), the somatic-marker hypothesis (Damasio, 1994) and its recent extensions to a winner-takes-all neural economics approach (Bechara, 2005; Bechara & Damasio, 2005) and the affect heuristic (Slovic et al., 2002), except that we took the extra step to test these theories at the level of the choice attribute. Using the SCR measures, the results provided physiological evidence supporting these heuristics. However, the current data also showed that combining ‘‘feelings’’ according to a proportional difference algorithm was more descriptive of the preference judgments. This leads us to conclude that the role of emotion in these situations is more specific than that suggested by the theories forwarding a general reference to feelings and/or an affective pool.

Thus, the current research has provided evidence that emotion can serve as an exchangeable quantity in preference formation. Emotion can be parsimoniously combined with explicitly quantified symbolic information through a proportional difference algorithm. The results of Studies 2 and 3 show that the addition of emotionally based importance weights bolsters the predictive strength of the basic PD trade-off algorithm.

The use of physiological measures in the current research advances the decision sciences in at least two ways. First, these data represent the first demonstration of an explicitly defined quantitative choice algorithm

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that utilizes symbolic and physiological arousal measures to predict strengths of preference. This is an interesting advancement in terms of how emotion may be quantified and traded in decision algorithms. Second, the use of these measures is interesting from a decision theory perspective. Peters (2006) has raised an important question to the decision-making literature by asking "how do we know it is emotion influencing choice?". Peters contends that individuals can have positive and negative thoughts about objects and events, and it is important for decision-making theory, to be able to separate the influence of thoughts from the influence of feelings. In order to parse these effects, Peters suggests the use of self-reported emotional measures as well as the use of physiological measures to identify emotional influences on choice. We feel the current demonstration that physiological measurements of arousal can be combined with non-physiological information to predict preferences, is strong evidence for a quantitative influence of emotionally rooted factors on decision-making.

The d^* SCR model was a significant predictor of preference in all three studies; however, the levels of accounted variance were relatively low when compared to other model fits of preference data in the decision-making literature. Nonetheless, it is important note that the d^* and AE SCR models tested here were completely specified, meaning that we did not estimate any free parameter values. This is important because we are specifying and testing theory-based structures of decision mechanisms from the function of emotion literature. This provides the desirable position of confirmatory hypothesis testing on specific mechanisms. We feel that this preferable to using solely an exploratory free parameter estimation approach wherein all inputs are entered into an equation and allowed to take on any form to maximize prediction.

In fact, some of the most interesting findings in the psychological literature come from insight gained in experiments that produced small, but impressive, effects (Prentice & Miller, 1992). The effect size of an experiment is dependent on the experimental setting and the operationalization of the variables. Study 2 provides a good example of this because the stimuli were constructed deliberately to have a d-level equal to 0 for every gamble pair in order to isolate the role of emotional weights. This isolation, however, has a penalty associated with it, which is the reduction of possible variability that would be observed with more varying trade-offs. Thus, a small effect in this paradigm may be very meaningful in isolating the specific contribution of emotion in preference. The fact that the tests from Study 2 show that d^* is significantly related to preference judgments, support the conclusion that emotion is a component that influences choice. This indicates that we are gaining new knowledge about influential decision factors, even with relatively low R^2 levels. Prentice and Miller (1992) make this argument more broadly in their discussion of how small effects can be impressive.

While we know of no other research that has attempted to correlate measured emotional responses to options with preferences in the manner that we have here, we do note a similar gambling study by Peters and Slovic (2000) that sheds positive light on the level of predictability of our models. These authors utilized the Bechara et al. (1997) gambling task as a way to associate emotional dispositions with risk-seeking versus risk-averse behavior. Peters and Slovic (2000) correlated individual behavioral inhibition system (BIS) scores with choices from potentially high-loss decks of cards, and reported an $R^2 = .08$ ($r = -.29$). In addition, individual extraversion scores were correlated with choices from potentially high-gain decks of cards with an $R^2 = .10$ ($r = .32$). Peters and Slovic attribute the relationship of the BIS/extraversion scores and preferences to different emotional sensitivities to losses and gains captured by the scales. Our results show a more direct relationship between emotion and preferences, and our R^2 values are at least as high as those found by Peters and Slovic (2000). We anticipate that the current findings, along with the building evidence around emotion as a decision mechanism (Peters, 2006) will spur significant advancements over the processes detailed here.

A definitive explanation of the difference in predictability between the SAM and SCR models cannot be forwarded here. It is possible that the SCR measures are simply noisier than the SAM measures. However, it is also possible that the SAM measures are capturing a cognitive appraisal outside of the emotion experienced

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by the individual, and that cognitive appraisal may have a stronger relationship to preference in this particular task.

The intriguing possibility exists that the SAM measures are in fact a measurement of a cognitively based reflective system, and that cognitive assessment is having a greater influence on preference formation than the emotional response captured by the SCR in this situation. Future studies should attempt to provide insight on these issues by parsing effects of physiological and explicit measures of emotion. An experimental design that distinguishes the two measures of emotion, and quantifies the effects of each within a decision-making algorithm would be a fruitful extension of the current work.

We see the present findings as supporting and extending several influential models in the emotion-based choice literature including the ‘‘risk as feelings’’ hypothesis (Loewenstein et al., 2001). In addition, the visceral factors (VFs) theory (Loewenstein, 1996) has provided a detailed theoretical account of the emotional influence on choice, and the current results provide support for this theory. A VF is defined as a behavioral factor that has a direct hedonic impact (i.e., pleasure or pain) and influences the desirability of different goods for consumption and various actions (Loewenstein, 1996). Examples of VFs include drive states (e.g., hunger, sexual desire), drug cravings, moods and emotions, and physical pain. The influence of the VF on behavior increases as the intensity of the VF increases. Loewenstein (1996) suggests that an understanding of a multitude of extreme behaviors that are not in the best interest of the individual can be gained by considering the influence of VFs (e.g., phobias, falling asleep at the wheel, drug addiction). The current research provides evidence for the influence of VFs on choice at these more moderate levels where emotions can be traded relative to the importance of outcomes to the decision maker.

Finally, these results should be interpreted within the context of recent advances in the neuropsychological literature. Montague and Berns (2002) have forwarded a neural economic model for object valuation. In their thesis, the orbitofrontal striatal (OFS) circuit is the centerpiece biological substrate for the valuation of disparate goods. That is, this area is actively involved in creating a common currency for valuing objects in the environment that do not reside on similar scales (e.g., are three apples equal to, better, or worse than four oranges). The authors present some interesting correlational data between the activity of a single neuron in the OFS of chimpanzees and the chimpanzee behavior in relation to rewards (e.g., raisins, apples, cereal). The data show a positive ordinal relation between the activity of the neuronal cell and the consumption behavior of the chimpanzees. The authors also cite evidence of how numerous other distinct stimuli (e.g., a woman’s face) all generate activity in the OFS. Montague and Berns (2002) interpret these findings to indicate that the OFS is creating a representation of value.

Recent theory related to the somatic marker hypothesis has fleshed out how this systems-based model may manifest in the neural circuitry (Bechara, 2005; Bechara & Damasio, 2005). These authors propose a dual systems approach suggesting an impulsive system, driven by the amygdala and related structures, and a reflective system, driven by the ventromedial pre-frontal cortex (VMPC). Affective neural state patterns can be generated by either system. The impulsive system is stimulated directly from the environment. Once an affective neural pattern has been generated, it is accessible through memory. The reflective system generates the activation of neural state patterns through memory or imagination. Once activated, these neural state patterns compete, in a survival of the fittest sense, with stronger patterns becoming reinforced and weaker patterns diminishing over the course of decision deliberation. In the end, the winner-takes-all, with the strongest signals winning the day and directing appropriate cognitive structures to take action.

In relation to the current thesis, these neural models are consistent with current model in the sense that they point to emotional valuation as a key component in decision-making. These models also posit that an overall assessment of value is generated by the decision maker, which is influenced by emotion and is ultimately directive of behavior. However, in both neural models, the incorporation of ‘‘colder’’ cognitive trade-offs into a mixed model including emotional valuation is not addressed. In the case of Montague and Berns (2002), it is not clear how higher cognitive assessments of value are combined with the reward-related affective activity they find in the OFS. In the case of the neural extension of the SMH, the higher order reflective system can

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influence decision-making, but it does so through the reactivation of an affective neural pattern, and the strength of that affective representation will determine whether it wins the day in the survival of the fittest neural competition model of value. Thus, in each case one has to assume that even the cold symbolic information is producing an affective reaction that is competing neurally with the affective information being generated from the ''warmer'' stimulus attributes. It is difficult to distinguish how the neural SMH model would incorporate trade-offs between ''cold'' symbolic information valuations and the valuations that create an affective pattern either from the impulsive or the reflective system.

It is possible that the symbolic trade-offs in our current model are in fact also affective, and are producing affective neural patterns, such that the neural SMH model can accommodate the current findings. However, it is also possible that the symbolic information inherent in our decision tasks, do not create an affective neural pattern and are effecting decisions in manner that is distinct from the SMH winner-takes-all process. Future research could explore this issue by assessing choice attributes that are commonly thought of as ''cold'' yet are still assumed to be influencing decision-making, and assessing the neural activity associated with the evaluation of these attributes.

We take our initial results as fruitful advances in understanding how symbolic and emotional information come together to influence preference judgments. In this nascent field, the results showing that these theoretically derived, fully specified, decision mechanisms were significant predictors of preferences across three disparate decision scenarios is an important empirical finding that should advance future research investigating the structure of decision-making mechanisms. Future research should seek to close the gap in explaining the variability of the judgments observed through further specification of decision processes. We have specified theoretically based emotion mechanisms as a way of setting base levels from which more comprehensive theories of emotions and preference can be built. We view these findings as an exciting step in the direction of incorporating emotion as a tradeable quantity, and we anticipate important future advancements from this initial foray.

APPENDIX A—PERSUASION MANIPULATION

Everyone makes decisions differently based on what is most important to them. We would like you to consider the following information and decide if it is important to you in the evaluation of potential dating partners. People generally use this data differently depending on their own personal preferences so please consider it only as it is important to you.

Research has shown that college men who rank higher on the IQ scale during college are more successful in their subsequent careers than men who score lower on the scale (Loughton & Jenkins, 1995). Specifically, college men scoring high on intellect earn an average of \$20 000 more per year than college men scoring in the middle on intellect, and college men scoring high on intellect earn an average of \$50 000 more per year than college men scoring low on intellect. These men, high intellects, also are more likely to assume roles of greater responsibility and enjoy positions of power during their careers, as opposed to men scoring mid to low on intellect (80 vs. 15 vs. 5%, high, mid, low, respectively). They are looked up to and often fill positions which families and communities respect and honor.

In addition, longitudinal studies which have surveyed women on their satisfaction with their relationship with their spouse have shown striking results. Women married to men scoring high on intellect are twice as likely to report happiness with their marriage and family life, fulfillment from their relationship with their partner, and contentment with their lifestyle. Self-reports suggested that these women felt their partners were more committed to their relationship and family and were more sensitive to their needs.

Finally, statistics from OU alumni indicate that over 60% of Ohio University graduates actually marry someone from OU. In addition, of that 60%, 85% of the couples actually dated during college. We will now proceed to the series of decisions.

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APPENDIX B

Study 2: Gamble stimuli pairs with mean strength of preference toward the risk-seeking option and mean model predictions

	Stimuli				Strength of preference		Model							
							d^*SAM		AE SAM		d^* SCR		AE SCR	
Context	*A* ($)	*B* ($)	*A* (*P*)	*B* (*P*)	*M*	*s*	*M*	*s*	*M*	*s*	*M*	*s*	*M*	*s*
Gain	$5	$4	0.08	0.1	−25.48	46.27	−0.01	0.09	−0.25	1.34	−0.03	0.15	−0.01	0.10
	$10	$8	0.08	0.1	−10.69	47.36	−0.04	0.08	−0.44	0.84	0.01	0.15	0.00	0.12
	$15	$12	0.08	0.1	−15.93	50.44	−0.02	0.08	−0.26	0.78	0.00	0.15	0.01	0.23
	$20	$16	0.08	0.1	2.94	47.44	−0.02	0.08	−0.25	0.94	−0.02	0.13	0.01	0.20
	$25	$20	0.08	0.1	0.69	51.55	0.00	0.08	−0.03	1.23	0.00	0.14	−0.03	0.16
	$30	$24	0.08	0.1	2.04	51.45	−0.04	0.08	−0.50	1.22	−0.01	0.13	−0.02	0.09
	$35	$28	0.08	0.1	−12.31	55.01	−0.02	0.06	−0.27	0.89	−0.01	0.13	0.02	0.24
	$5	$4	0.4	0.5	−17.89	54.06	−0.05	0.12	−0.43	0.89	0.00	0.16	0.04	0.22
	$10	$8	0.4	0.5	−24.17	45.02	−0.06	0.13	−0.41	1.11	−0.07	0.14	−0.08	0.26
	$15	$12	0.4	0.5	−27.83	42.86	−0.06	0.09	−0.42	0.74	0.00	0.14	−0.01	0.14
	$20	$16	0.4	0.5	−5.50	49.08	−0.01	0.09	0.03	0.85	−0.02	0.14	−0.02	0.13
	$25	$20	0.4	0.5	−33.30	44.45	−0.04	0.09	−0.42	0.75	0.01	0.15	0.00	0.14
	$30	$24	0.4	0.5	−24.19	48.27	−0.11	0.09	−1.53	1.61	−0.08	0.13	−0.05	0.13
	$35	$28	0.4	0.5	−15.30	48.27	−0.03	0.08	−0.35	1.04	−0.01	0.15	−0.03	0.22
	$5	$4	0.8	1	−55.52	58.45	−0.02	0.04	−0.43	0.68	−0.04	0.13	−0.02	0.14
	$10	$8	0.8	1	−71.46	49.59	−0.02	0.04	−0.65	0.83	0.02	0.13	0.01	0.08
	$15	$12	0.8	1	−61.22	55.56	−0.03	0.03	−0.87	0.74	−0.03	0.13	−0.01	0.15
	$20	$16	0.8	1	−50.87	63.86	−0.02	0.02	−0.51	0.73	0.03	0.13	0.02	0.15
	$25	$20	0.8	1	−76.31	42.65	−0.03	0.03	−1.02	0.75	−0.03	0.13	−0.04	0.13
	$30	$24	0.8	1	−68.00	47.93	−0.02	0.02	−0.77	0.65	0.04	0.14	0.04	0.23
	$35	$28	0.8	1	−67.54	55.55	−0.03	0.03	−0.96	0.86	0.00	0.15	0.02	0.16
Loss	−$5	−$4	0.08	0.1	33.17	54.21	0.02	0.08	0.42	1.00	−0.05	0.13	−0.03	0.07
	−$10	−$8	0.08	0.1	26.22	53.82	0.04	0.07	0.36	0.63	0.04	0.14	0.02	0.14
	−$15	−$12	0.08	0.1	28.39	53.25	−0.01	0.08	−0.11	1.23	−0.02	0.15	−0.02	0.15
	−$20	−$16	0.08	0.1	11.13	58.78	0.02	0.10	0.20	0.88	0.04	0.12	0.06	0.17
	−$25	−$20	0.08	0.1	15.76	58.23	−0.01	0.07	−0.20	0.87	−0.01	0.15	−0.02	0.16
	−$30	−$24	0.08	0.1	13.56	58.50	0.03	0.09	0.30	0.97	0.02	0.14	0.02	0.18
	−$35	−$28	0.08	0.1	22.37	55.94	0.01	0.09	0.21	1.12	−0.03	0.14	−0.02	0.13
	−$5	−$4	0.4	0.5	22.85	50.10	0.05	0.12	0.48	0.99	0.04	0.15	−0.01	0.13
	−$10	−$8	0.4	0.5	35.81	41.21	0.04	0.10	0.20	0.66	0.01	0.13	0.04	0.16
	−$15	−$12	0.4	0.5	23.30	44.60	0.03	0.10	0.24	0.55	0.02	0.14	0.04	0.21
	−$20	−$16	0.4	0.5	11.17	46.12	−0.01	0.10	−0.15	1.07	−0.02	0.15	0.00	0.11
	−$25	−$20	0.4	0.5	18.15	41.63	0.04	0.09	0.21	0.96	0.00	0.15	−0.02	0.12
	−$30	−$24	0.4	0.5	23.44	46.99	0.10	0.10	1.34	1.60	0.09	0.14	0.06	0.14
	−$35	−$28	0.4	0.5	10.17	48.44	0.03	0.07	0.28	0.83	0.02	0.14	0.02	0.13
	−$5	−$4	0.8	1	56.07	49.68	0.00	0.08	0.32	0.99	0.02	0.15	0.06	0.22
	−$10	−$8	0.8	1	69.56	39.07	0.02	0.05	0.74	1.56	−0.04	0.13	0.01	0.14
	−$15	−$12	0.8	1	59.17	44.99	0.04	0.05	1.04	1.27	0.03	0.13	0.02	0.20
	−$20	−$16	0.8	1	53.46	49.51	0.02	0.05	0.49	1.15	0.00	0.15	−0.04	0.18
	−$25	−$20	0.8	1	55.81	49.88	0.03	0.04	0.84	0.96	0.05	0.12	0.05	0.14
	−$30	−$24	0.8	1	48.17	49.42	0.02	0.03	0.49	0.86	−0.03	0.13	−0.03	0.26
	−$35	−$28	0.8	1	56.48	49.72	0.02	0.02	0.66	0.61	0.01	0.12	0.01	0.10

There are 21 choice pairs (seven outcome by three probability levels) at a single *d*-level (0) within gain and loss conditions.

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