Aspects of the Interplay of Cognition and Emotion and the Use of Verbal vs. Numerical Information in Decision Making.

Doctoral dissertation

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I dedicate this work to my family and in

particular to my wife, Angela.

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PROLOGUE

When I was planning to apply to graduate school, I used to spend long periods of time questioning the behavior of people at the office and also of our clients. By that time I was a junior consultant in a multinational firm. At work, I routinely interacted with different teams within the working staff as well as with various types of corporate clients. I was constantly intrigued by the particularities of people's behavior, regardless of their rank within companies. It was somehow disturbing to realize that executives' decisions seemed extremely influenced by personal traits and an undeniable subjectivity. Those thoughts triggered my initial interest in decision making and its behavioral nuances. I ignored then that there is a wide and active research field of research devoted to the behavioral side of decision making.

Some months later, during the early stages of the GPEFM program, I discovered that the interesting issues of managerial decision making that intrigued me, could be understood as a subset of a wider spectrum of decision making that included everyday decisions. It was also surprising to learn that the study of decision making is a mixture of thought schools and academic disciplines. Decision making revealed itself as a non trivial activity that goes beyond some highly important decisions that we make in life, such as getting married or buying a house. Decisions are at the core of human nature as our life is, in the words of Read Montague (2006; pp vii) a "compilation of billions of choice moments where one outcome is selected and others forgone". In spite of their relevance, the forces that shape decisions and the processes that support them are aloof and hidden. They are rooted in the intersection of instincts, free will and the limitations of our brain. This poses a challenge for scientists.

My first approach to the problems of decision making was related to the role of human values. They serve as a guiding light for decisions, as pervasive policies that ultimately determine the actions that are consistent with our deepest goals. However, the study of values is complex and can easily lead the researcher into ethical and deontological waters. My questions came from a different perspective. They were related to the mechanisms that people use to include their values in the set of information and cues that are processed while making decisions. What is the shape of a human value in the mind of a decision maker? My thinking process directed me to conceptualize values in two ways. First, values are categorical, even dichotomous variables. Second, values trigger emotions. In simple words, an alternative is (feels) either in accordance with a certain value or against it. This idea took me to the broader question of how we process any type of categorical information and what are the affective components of such process. Things in the world are large, small, far, correct, etc. People make these kinds of judgments constantly and these judgments precipitate our actions. Am I driving too fast? Is it already late? Is this house big? Was that meal tasteful? Categories are full of meaning, and such meaning is colored by our feelings. However, the world is full of complex numerical pieces of information that require training to handle. Consumers in particular face the challenge of interpreting numerical information and determining its meaning. Feelings are part of such meaning.

The two chapters of this dissertation were motivated by these ideas. In the first, I propose and test a model of how people understand numerical information and transform it into categories. I unveil some of the forces that shape this categorization process and elaborate on the implications and importance of this transformation for decision theory, the psychology of categorization and consumer behavior. The second chapter explores the role of affect in decision making and whether the distinction of numerical/verbal information is relevant for that role. I develop and test four decision models that capture the interaction of affective and cognitive information. I manipulate categorical and numerical expressions of attributes. In this chapter I reveal novel properties of the role of affect in decision making and its interaction with cognitive processes.

In summary, the present doctoral dissertation contributes to advance knowledge in behavioral decision making with applications to marketing. In particular I contribute to the understanding of categorization processes and the interaction of cognition and emotion during the construction of preferences.

REFERENCES

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ABSTRACT

The present dissertation investigates two aspects of decision making: First, I study the way in which people, in particular consumers, understand and categorize numerical attributes of products. In this chapter, I develop and experimentally test a model of the mental process of the way people transform a quantitative attribute into a verbal category. Under certain environmental conditions, the model is able to predict the verbal conceptualization of people. This model is of value to decision making and marketing theorists as well as marketing practitioners.

Second, I explore the interconnections of cognitive and emotional information during the process of decision making. In this chapter I propose and experimentally test four different models of the way cognitive and affective information is combined during the decision making process in order to determine the value of an alternative. The models display a high predictive power. The performance of the models is influenced by (1) the interaction of verbal and numerical information with the situational cognitive capacities of the individual and (2) by the correlation of cognitive judgments and affective reactions.

Following is a detailed abstract of each chapter.

Chapter One

To understanding quantitative attributes of choice alternatives, consumers often need to map quantities into dichotomies (e.g., whether a car is fast or slow). This work explores the process in which consumers engage in order to make sense out of numbers. I conceptualize

this process through a model of the inherent uncertainty that is present in such a categorization process. I call this the categorization uncertainty (CU) model. This model is able to predict the categorization of quantitative/continuous attributes based on (a) the fuzzy nature of categories and (b) the range sensitivity of the categorization judgments. In the present chapter, I develop and experimentally test the validity and applicability of the CU model. Results show that based on the model of categorization uncertainty (CU), membership judgments at the attribute level can be accurately predicted using the mean and standard deviation of the quantitative range being dichotomized. Implications are discussed for categorization processes, marketing and the psychology of multiattribute choice.

Chapter Two

The combined role of affect and cognition in decision making has received wide but scattered attention by decision theorists. As a result, the literature does not provide an account of how the way in which people mix cognitive and affective information influences the construction of preferences. It has been only speculated that people may monitor their feelings while making decisions (e.g., Pham 2004). In the present chapter, I extend the notion of "monitoring" to "procedural preferences". This is, that people may choose, consciously or unconsciously, particular procedures to combine cognitive and affective information during decision making. Grounded on this idea, I propose and test four decision making models that capture different alternatives of the integration of affect and cognition in decision making. The models are able to predict people's choices well and their performance is found to be affected by procedural preferences. These are rooted in (1) the depletion level of cognitive capacities, (2) the consistency of information and (3) the correlation of cognitive judgments and affective reactions. The analysis of the models provides insights into the use of various types of emotions. Building on those results I propose a general conceptualization of the role of affect in the construction of preferences, along different stages of the decision process. In addition, I offer several research paths that follow these results.

Chapter 1:

Categorization of Quantitative attributes: How Consumers Understand Quantitative Information?

INTRODUCTION

Imagine a consumer that decides to buy a new laptop computer. She wants a computer that is fast, good for multimedia content, not too heavy and offering an extended warranty. With these goals in mind she goes to the store and finds that computer specifications are expressed as megabytes per second, total megabytes of RAM memory, megabytes of graphic capacity, kilograms and months covered by the warranty. From all this complex information (and luckily some vague guidance from a sales person), she must evaluate which computer meets her goals. In this paper I investigate what consumers do in order to understand quantitative/continuous attributes and the particularities of this process.

As the example illustrates, consumers often need to interpret quantitative/continuous attributes of products in order to determine whether the product has a certain feature or not (e.g., whether a car is fast or not). It is usual that certain attributes are expressed quantitatively, like the weight of a mobile phone, or the durability of its battery, and it is the consumer’s job to determine whether the phone has a durable battery or whether it is heavy. The importance of studying how people map quantitative information into categories is twofold. First, from a psychological point of view, it sheds light on how people process different types of information during decision making, and second, from the consumer behavior perspective, it helps to understand categorization processes at the attribute level, which is relevant to determine subsequently the membership of a good to different product categories (e.g., how fast a meal should be served and how expensive the meal should be in order to consider a restaurant a member of the fast food category?).

Categorization processes have been widely studied at the object level but less often at the attribute level (see review in Viswanathan and Childers, 1999). There is limited knowledge on how consumers mix continuous attributes with features to issue a product categorization judgment. Consumer psychology has emphasized the importance of feature-based judgments of fuzzy categories of products (Medin and Smith, 1994) as well as the relevance of feature level comparisons to determine the similarity of objects (Tversky, 1977). However, it is not clear whether numbers and features are directly combined or consumers instead make an effort to interpret (categorize) quantitative attributes in terms of features and then do the product categorization using mostly features. I argue that most quantitative attributes are "featurized" before the product categorization takes place. Therefore, the present study contributes to understand product categorization by investigating the process by which consumers encode quantitative/continuous information to determine whether a desired feature is present or not (e.g., if a consumer wants a small mobile phone, how she decides which phones possess that feature and should be included in her choice set).

At the decision making level, the present research offers results that help to understand the cognitive processes involved in making sense of the various and ambiguous meanings that verbal and quantitative information may imply for individuals, the mental processes people employ to think in terms of categories and quantities, and the effects of such ambiguity on judgments and decision behavior.

In this chapter I investigate the characteristics of the process by which people map quantitative/continuous information into binary categories (dichotomies) by introducing the notion of categorization uncertainty (CU). This represents the struggle people experience when trying to determine the categorical membership of a given number. The categorization uncertainty (CU) concept allows the proposal of a model of the categorization process based on two components; (i) the fuzzy nature of categories and (ii) the sensitivity of categorization judgments to the quantitative range evaluated. This model is able to predict categorization judgments of quantitative attributes. The chapter is organized as follows: First, I provide a brief review of relevant literature on the problem of numbers and categories, the range sensitivity of categorization and the fuzziness of categories. Second, I introduce the notion of categorization uncertainty and the model of the categorization process. Third, I present experimental work testing the main ideas proposed, the predictive power of the model and its value as a marketing tool, and finally, I discuss results in terms of implications for consumer behavior and the psychology of categorization processes.

BACKGROUND

Quantitative and verbal representations of attributes.

The most extensive work on verbal-quantitative expressions of attributes comes from research on the communication of uncertainty and probabilities (Wallsten, 1990; Gonzalez – Vallejo and Wallsten, 1992; Gonzalez-Vallejo, Wallsten and Erev, 1994). This work (among others) revealed for instance that verbal probabilities are seen to be processed differently and more consistently than quantitative ones. In addition, the average quality of decisions made using verbal probabilities was not inferior to that of decisions made using quantitative probabilities. Wallsten, Budescu, and Zwick (1993) argue that decision performance is not affected by using quantitative or verbal probabilities. Note that this literature is mainly focused on studying the differences on decision outcomes when one format or the other is used. However, people may perform the quantitative/categorical mapping task in order to categorize the quantitative probability into something easier to understand. Evidence of this are the findings of Budescu, Karelitz and Wallsten (2003), who found that people prefer to communicate probabilities linguistically, due to the richer meaning of verbal expressions and the directionality that is easily implied from them.

Supporting the notion that people attach more meaning to categories than to quantities, some researchers have investigated choices using both numbers and words to describe the same options. They found several and multiple effects. For example, it is claimed that people may judge and compare quantitative attributes superficially, without considering the actual meaning of the information, even when trained to do the verbal-quantitative mapping (Viswanathan and Narayanan, 1994). This implies that the quality of judgments is reduced if quantitative attributes are used. Similarly, the consistency of decisions and judgments, their complexity and how they are communicated, are found to be more favorable when using a verbal as opposed to a quantitative decision system (Larichev and Brown, 2000). Hogarth and Einhorn (1992) found that verbal and quantitative information triggered different belief-updating processes. In addition, Hsee, Zhang, Yu and Xi (2003) found that when people overweigh quantitative attributes only to justify decisions based on the belief that “rationalistic” (i.e., quantitative) attributes are more important than qualitative ones, a conflict between predicted and actually experienced utility occurs. Lindberg, Garling and Montgomery (1991) argue that quantitative information is more significant for choices than verbal, but that may be due to the same naïve rationalism.

In summary, there is significant evidence to motivate research on the idea that people must perform some process to map quantitative information into categories in order to assimilate information in an intelligible way. The full characterization of such psychological phenomena is beyond the scope of this chapter, but the results presented here contribute to this goal.

Range Sensitivity

Categorization judgments and processes are complex, diverse, contingent and subject to individual differences (Cohen and Basu, 2001). One of these contingencies, specific to categorization judgments over a quantitative scale, is the influence that the quantitative range being evaluated may exert on the way people assign category membership. In principle, to produce a meaningful categorization, the mental frame of comparison should be established through the proper disclosure of the global range of each quantitative attribute (Parducci, 1965). This way, in order to obtain true categories from people regarding what is fast, big etc., the global range of the scale over which such categories are being defined should be observable. Nevertheless, global ranges are extremely difficult to determine (if at all) for most attributes. As a consequence, most categorization judgments people use to make decisions are issued over partial ranges which potentially bias such judgments. Thus, keeping cultural and environmental variables controlled, any given numerical value of an attribute could be assigned to different categories depending only on the range in which that number is included. This principle of *range sensitivity* is not explicitly stated in the categorization literature, therefore I shall provide empirical proof of its existence.

For the purpose of this research, I shall use attributes that can be expressed both on a continuous scale and as a dichotomous or binary category. I restrict analysis to this type of category for the following reasons: First, dichotomization is a common and relevant mental process for people trying to establish meaning out of attribute information. For example, when trying to determine the presence of a feature from a quantitative expression of an attribute (e.g., whether a house is expensive or not, or whether a job location is near or not). And second, other categorization of quantitative information where values are mapped in an ordered set of categories (i.e., a five or seven point scale) are basically reductions of inherently continuous information using verbal quantifiers, whereas dichotomies are true categories that maximize the differentiability of meanings. Dichotomies can be seen as the simplest and most extreme form of categorization .

Membership Functions and Fuzzy set measures of category membership

The issue of the comparability in meaning between numbers and categories can be conceptualized through the idea that any number on a measurement scale (e.g., speed) can be related to a category (e.g., fast) at least to some extent, given that categories have graded structure and therefore are basically fuzzy sets (Viswanathan and Childers, 1999). For example in assessing the vague meanings of probabilistic phrases, Wallsten et al. (1986) (also see Budescu et al., 2003) measured the degree of membership of a quantitative probability to a categorical one using a concept drawn from fuzzy set theory: the method of membership functions. In this method, people report in the closed $[0,1]$ interval, the likelihood that a quantitative probability belongs to a verbal probabilistic category (e.g., highly probable). This approach effectively captures, at the individual level, the relative vagueness of the probabilistic phrases. In terms of categorization, membership functions resemble to some extent the processes of categorization by prototypes, in which a target item is compared to an ideal category member and from that comparison a degree of membership to the category is estimated (Cohen and Basu, 2001). Viswanathan and Childers (1999), developed two fuzzy set measures of product category by aggregating membership at the attribute level, for continuous (i.e., quantitative) attributes. They claim that given that categories are fuzzy sets, products vary in their degree of membership according to the membership on some attributes that are components of the category. For example, for a car to be considered in the economy category, attributes like gas mileage and price should have certain values. I extend the notion proposed by Viswanathan and Childers (1999) by exploring the process by which people decide, looking at the degree of membership, whether an attribute's quantitative value constitutes a certain feature or not. Viswanathan and Childers make no statement regarding how people derive meaning from the continuous attributes, they just aggregate membership judgments over several attributes. My contribution over their work is to propose a model of categorization at the attribute level which is able to predict category membership based only on the characteristics of the quantitative range being categorized.

THE MODEL

To conceptualize the process of categorization, I introduce the notion of what I call "categorization uncertainty"(CU). This concept captures the psychological struggle people experience in the process of mapping a number into a category. For instance, imagine you are asked to state whether a 25 minute waiting time at a given restaurant is long or short? You probably do not have an immediate answer. There will be a deliberation process during which you will have some feeling of uncertainty. If I increase the number to 180 minutes or if I decrease the number to 2 minutes, the categorization is much easier (i.e., less uncertain). Similarly, there must be a number (e.g., 15 minutes) that is extremely difficult to categorize. For such a number, the categorization uncertainty reaches a maximum, because you do not know to which category it belongs.

I argue that this experience of uncertainty can be modeled and measured. Specifically, categorization uncertainty (CU) is *a representation of how much uncertainty people experience in mapping quantities of a scale into a dichotomy*. CU takes values in the $[0,1]$ interval, where 0 means that a person is absolutely sure about the category membership (e.g.,180 minutes waiting in a restaurant is long) and 1 means that a person is completely *un*sure (e.g., 15 minutes waiting) to the point of assigning the category at random.

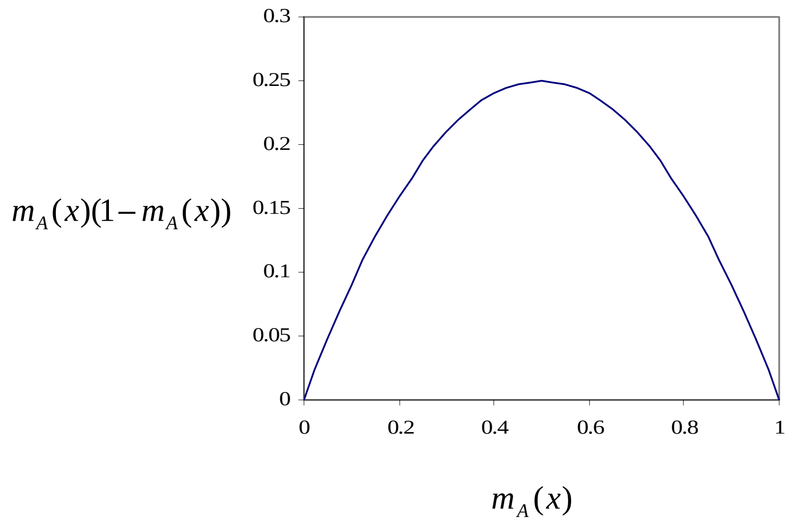
The intuition behind the model resides in the fact that the categorization process can be expressed as the interplay of the degree of membership of a certain value to category, A, with the degree of membership to category, B where A and B are two sides of a dichotomy (e.g., fast, slow). As the difference between the memberships decreases, the categorization uncertainty increases; while if the difference increases, categorization uncertainty decreases.

I state the model at the individual level. Let us start by recalling that the characterization of the membership judgments can be made similarly to membership functions (Wallsten, 1986). As mentioned earlier, in membership functions people report in a $[0,1]$ interval, how likely, for example, a quantitative probability matches the meaning of a verbal probability. Generalizing this idea to any scale and category, not only probabilities, let $m_A(x)$ denote the membership judgment that value *x* belongs to category *A*. Also, let $m_B(x)$ denote the membership judgment that the same value *x* belongs to category *B*. What we have is basically the aggregated membership judgment for value *x* with respect to two sides (*A* and *B*) of a dichotomy (e.g., large vs small). Note that if there is a $m_A(x)$, there is also the complementary membership that *x* does *not* belong to category *A*, i.e., $1 - m_A(x)$.

This way, if a person is, for instance, completely sure (not uncertain) that *x* belongs to *A*, then $m_A(x) = 1$ and $1 - m_A(x) = 0$. In the case of maximum uncertainty, the complementary membership judgments are indistinguishable from each other and therefore $m_A(x) = 1 - m_A(x) = 0.5$. The next step is to capture in one single term, the total uncertainty of the membership judgment. To do that, among the possible mathematical interactions of the complementary membership judgments $m_A(x)$ and $1 - m_A(x)$, the product of the two, $m_A(x)(1 - m_A(x))$, has the property of being zero when the judgments are either zero or 1, and maximum (0,25) when they are equal[1], hence providing a measure of the implicit uncertainty of the categorization judgment for value *x* with respect to category *A*. In general, let us call such uncertainty $U_A(x)$, where $U_A(x) = m_A(x)(1 - m_A(x))$ and its behavior is graphically displayed in figure 1. Summarizing, the uncertainty expression $U_A(x)$ will be 0 (no uncertainty) if the membership judgment $m_A(x)$ is either 0 or 1, and it will take a maximum value of 0.25 (maximum uncertainty) if the membership judgment is 0.5.

[1] The sum of the two complementary judgments is always = 1, providing no information on the total uncertainty. The division, on the other hand, is affected by the order producing two different uncertainty measures for equivalent pairs of judgments. That would be an ambiguous measure.

Figure 1. Membership judgment and its associated uncertainty.



So far, there is a representation of how uncertain a person is, that *x* belongs to category *A*. However, this doesn't capture yet the categorization uncertainty of the process itself. To obtain such a model, the uncertainty related to each candidate category must be considered. The rationale is the following: if it is difficult to assign *x* to one category (*A*) but not to the other (*B*), the process of categorization is not uncertain. However, if it is difficult to assign *x* to either of the considered categories (*A* and *B*), the process becomes uncertain. Note that assignment to categories *A* or *B* is assumed to be negatively correlated but independent in nature at the individual level. That means that the assignment of *x* to each category can be made separately, and there exists the possibility that an individual judges that *x* has low membership in both categories. For example, to say that 160 Km/h is not fast does not automatically mean that it is slow. (I shall elaborate a little bit more on this point later on). On the basis of independence of judgments at the individual level, the simplest approach to formalize the complete categorization process is to add the membership uncertainty of *x* with respect to category *A*, ($U_A(x)$), to the membership uncertainty of *x* to category *B*, i.e, $U_B(x) = m_B(x)(1 - m_B(x))$, which is derived in the same way as $U_A(x)$. By adding the membership uncertainty of the same value *x* with respect to two categories, we have a representation of the uncertainty of the categorization process that leads to the assignment of *x* to a category. This way, an expression of categorization uncertainty (CU) would be:

$$CU(x) = U_A(x) + U_B(x) \tag{1}$$

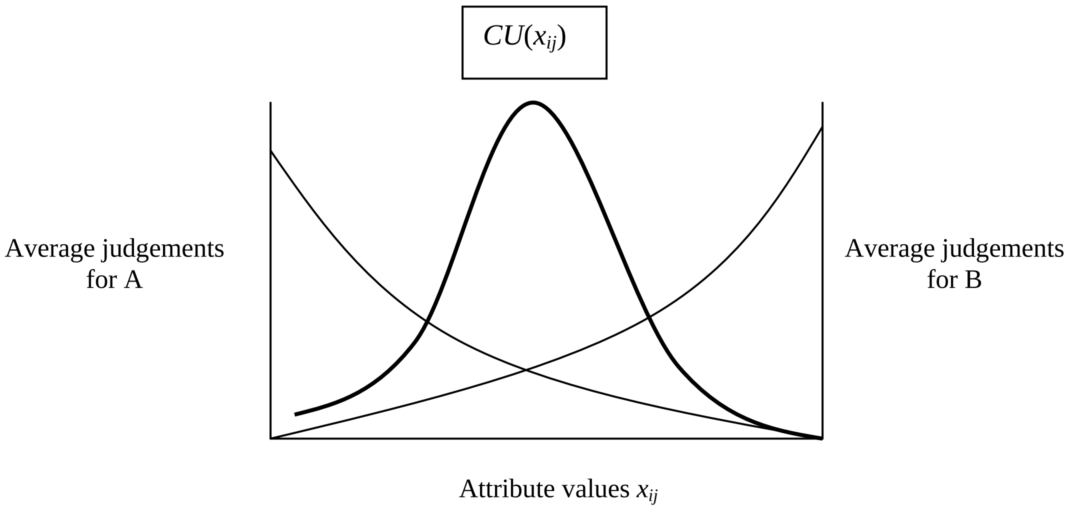
This expression however, yields values between 0 and 0.5, because the maximum values of $U_A(x)$ and $U_B(x)$ are 0.25 respectively. Therefore, to produce a measure of CU within the [0,1] interval, equation (1) can be normalized, yielding:

$$CU(x) = 2[U_A(x) + U_B(x)] \tag{2}$$

This expression captures the notion of uncertainty derived from the fuzzy nature of the opposite categories that constitute a dichotomy in a [0,1] interval, for any attribute value *x*. To complete the model, the range of values that *x* can take must be included, and thus the range sensitivity assumption is operationalized. For that purpose, let us define that R_j is a set of *n* possible values an attribute can take over a possible range *j*: $R_j = \{x_{1j}, x_{2j}, ..., x_{nj}\}$. For each x_{ij}, and categories A and B, people issue membership judgments $m_A(x_{ij})$ and $m_B(x_{ij})$. This step completes the model at the individual level.

To move to the aggregated level, membership judgments are then averaged across people to produce a curve that shows how they "agree" on the membership of every x_{ij}. Graphically, figure 2 displays the expected behavior of the aggregated model. On the horizontal axis we have the different x_{ij} for a given range R_j, and in the two vertical axis we have the average membership judgments: $\frac{\sum_{1}^{n} m_A(x_{ij})}{n}$ for category A in the left axis and $\frac{\sum_{1}^{n} m_B(x_{ij})}{n}$ for category B in the right axis. The assumption of negative correlation between membership judgments to A and B generates the symmetry of the average membership judgments displayed in figure 2, despite the possibility of independent membership judgments at the individual level.

Figure 2: Behavior of categorization uncertainty.



Finally, I use the average membership judgments to estimate U_A and U_B and replace those values in equation 1 to find the CU value for each x_{ij}.[2] The CU distribution expected would be like the one in figure 2 where, for the middle values of x_{ij} the uncertainty is high, and for the extreme values of x_{ij} the uncertainty is lower. The range sensitivity principle causes the CU curve to move along with the range over which it is defined, being centered on the mean value of this range.

The rest of this paper is devoted to testing the CU model. There are three experiments. The first checks the validity of the basic assumptions using a within subject design as well as how well the model fits empirical data. The second challenges further the validity of the model by changing the setting to a between subjects design and testing the boundaries of the assumptions. Finally, the third explores the applicability and predictive power of the model in a marketing setting.

EXPERIMENT 1

This experiment is aimed at testing the basic premises of the CU model, namely, the hypothesized shape of the CU curve based on the fuzziness of categories and the displacement of the curve caused by range sensitivity.

Method

The task. I first selected some attributes of products and situations that could be easily expressed with numbers and dichotomies: 2 attributes of laptop computers (weight and

[2] At the aggregated level, another measurement of uncertainty could be derived from the variance of the sum of the individual membership judgments of category A and B, yielding that $CU \approx \mathrm{var}(m_A(x) + m_b(x))$. However, even though this expression is conceptually similar to CU at the aggregated level, the CU formula provides a much smoother and more tractable representation of uncertainty. See an example in appendix 1.

battery duration) and 2 attributes of job offers (location of job and training)[3] . A quantitative scale and a dichotomy were defined for each attribute (see appendix 2).

Based on the scales chosen, two different ranges (R_1, R_2) of 15 values each (the x_{ij}´s) were defined for each attribute. The two ranges of each attribute were in turn defined over the same scale and one was a transformation of the other (i.e., range 2 = range 1*1.5, except for job training where, to generate credible numbers with noticeable difference, range 2 = 0.5*range 1) [4]. This way, the low end points of the ranges were close to each other and the high points more separated.

A within subject design was used. Participants were randomly assigned to one of two groups. Group 1 completed the task for range 1 (R_1) across all attributes, and group 2 completed the task for range 2 (R_2). To obtain the membership judgments, for each range participants were asked to establish on the [0,1] interval to what extent each number in the range would be considered a member of category A and also for category B (e.g., for computer weight, category A was "light" and category B was "heavy"). An answer of 1 means "complete" membership of the category under evaluation and 0 means "no membership at all". Participants could indicate any number between 0 and 1. This procedure was followed for each value within the range, and for each category (see appendix 2 for a complete list of scales, ranges and categories). By doing this, estimates for all $m_A(x_{ij})$ and $m_B(x_{ij})$ were obtained and the categorization uncertainty (CU) of each dichotomy and range calculated.

[3] These 4 attributes were selected from a larger list, including other goods. This short list was finally defined in order to have a set of attributes that lay people would normally understand. Technical attributes were not used.

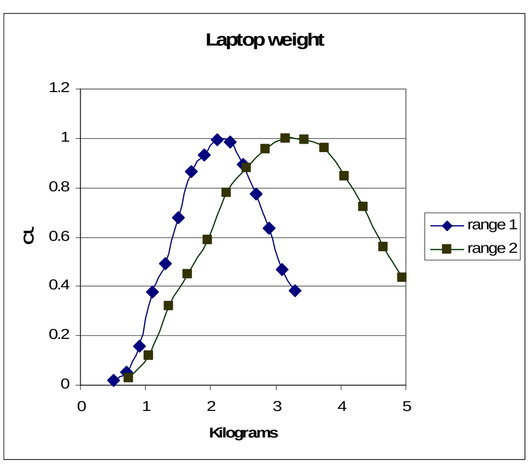
[4] The basic criterion to define the ranges was to use feasible values.

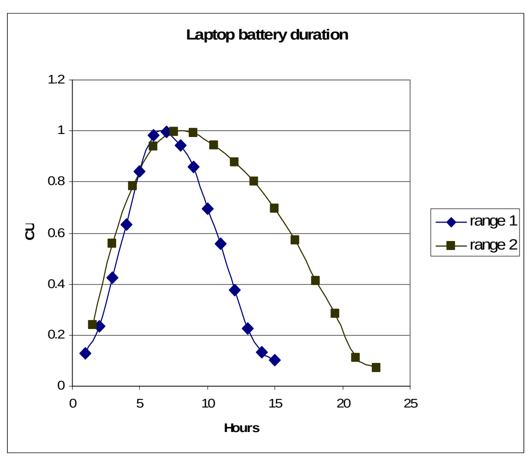
Subjects. 71 undergraduate students at UPF completed the task. They were recruited trough announce on campus. There were 36 in group 1 and 35 in group 2. Their average age was 20 years, 31% men and 69% women. They received a flat fee of 5 euros for their participation. It is important to note the cultural and environmental homogeneity of the sample. This guarantees that certain referents are similar, for example, since they all live in the same city, the referent for how far a given place is located, measured in minutes by metro, should provide the same context for all.

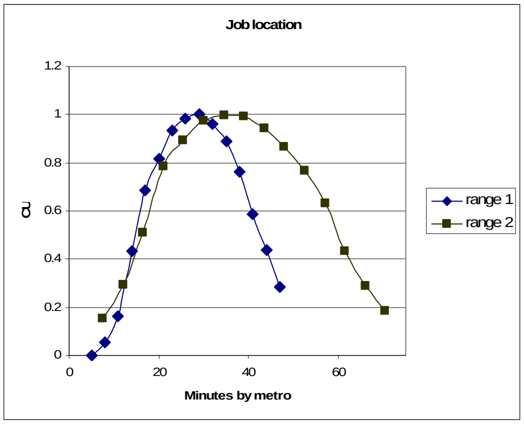
Results.

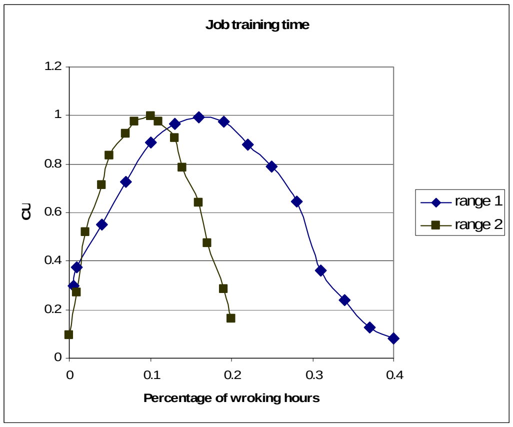
I first looked at whether the actual CU distribution follows the hypothesized shape (see figure 2) and to what degree the empirical CU curves move, without altering their shape, along different ranges. To do this, I plotted the empirical CU values against the different scales, within which the ranges are contained. In each graph, the two ranges are represented as well as their corresponding CU.

Figures 3.1 to 3.4. Categorization uncertainty by range.









The graphs show qualitatively that (1) the empirical CU distributions follow the shape hypothesized and (2) that they were clearly affected by the range over which people performed the dichotomization task. For example, we can see how, in job location, for a value near 45 minutes in range 1, people had low uncertainty (around 0.3) about the category (far). But in the wider range, for 45 minutes, uncertainty is almost 1, so participants in this group were unsure whether a 45 minutes trip to work is near or far. Bear in mind that all subjects are of a similar age and live in the same city. In general the trend is clear and for all four attributes the wider ranges affected the categorization judgments in the same direction. These results support the idea that categorization judgments can be modeled with the notion of categorization uncertainty, and that the assumptions of range sensitivity and fuzzy categories are reasonable. Note that if the fuzziness assumption was incorrect and people had crisp membership judgments, these would be either 0 or 1, producing a step membership and 0 uncertainty. Similarly, if range sensitivity was incorrect, the uncertainty of a given value would have remained the same across ranges. This means that from the uncertainty displayed by the subjects it seems that they generally lack absolute quantitative references of simple, every-day categories like those used in the experiment.

Predicting categorization judgments.

I now test whether categorization judgments can be accurately predicted using only the characteristics of the ranges. To do that, I compare the empirical CU curves to predicted CU curves based only on the range information. The hypothesis is that each pair of curves (i.e., the empirical and the predicted) for every range, are statistically the same curve. I approach it in the following way. I first determine whether the empirical CU curves behave as normal probability distributions. Second, I generate theoretical normal distributions with parameters (i.e., mean and standard deviation) taken from the range's mean and standard deviation. Finally I compare the two distributions.

Step 1: I performed a series of OLS (ordinary least squares) non-linear regressions on the CU cumulative distributions, fitting a cumulative normal distribution to each CU curve, for all attributes and ranges. Table 1 summarizes the results. Note the remarkably high value of all R^2 statistics. The estimated mean and standard deviation of the fitted normal distribution are also reported as well as the range's mean and standard deviation. There are strong similarities between these values, but the standard deviations suggest that the fitted normal distributions are slightly tighter than CU curves. However, the conclusion is that a normal distribution is a close approximation of an actual CU curve.

Table 1. OLS non-linear regressions on all attributes and ranges.

Set of ranges 1					
Attributes	**R2**	**Estimated mean**	**Range mean**	**Estimated SD**	**Range SD**
Laptop weight (*Kilograms*)	0.99	1.9	1.9	0.5	0.9
Laptop battery duration (*hours*)	0.99	7.7	8	2.1	4.5
Job location (*minutes by metro*)	0.99	23.9	26	5.8	13.4
Job training (*proportion of work*)	0.99	18%	19%	0.5%	13%

Set of ranges 2					
Attributes	**R2**	**Estimated mean**	**Range mean**	**Estimated SD**	**Range SD**
Laptop weight (*Kilograms*)	0.99	2.9	2.8	1.2	1.3
Laptop battery duration (*hours*)	0.99	12.6	12	5.9	6.7
Job location (*minutes by metro*)	0.99	36	39	17.6	20.1
Job training (*proportion of work*)	0.99	9%	10%	0.5%	6%

Step 2. I generated a normal distribution for each range. These estimated distributions are expected to approximate the actual CU distributions and will give an idea of the predictive power of the CU model. Since the OLS regressions produced such high R^2 values, to assess the predictive power of the estimations, I tested the hypothesis that each pair of normal distributions (the fitted from the regressions and the generated from the range parameters) are not significantly different. To do that, I performed a Kolmogorov Smirnov non-parametric test comparing the two distributions[5]. No significant differences were found. (The test produced $p > 0.9$ for all attributes). This means that the predicted CU distributions are not significantly different than the actual CU distributions suggesting a strong predictive power of the model.

This experiment presents some limitations because of the within subjects design. Remember that each participant produced membership judgments for both categories A and

[5] Kolmogorov-Smirnov test performs a non-parametric comparison of the values of two discrete cumulative distributions and its value refers to the probability that the two distributions are the same.

B simultaneously. This condition may have lead participants to be falsely consistent in their answers (i.e., if membership in A is high, then membership in B should be low) generating therefore the expected symmetry of membership judgments as a result of the experimental task. However, the alleged artificial consistency of people only affects the symmetry of the curves. It has no implication on the range sensitivity displayed and on the fuzzy nature of the categories underlying the answers.

EXPERIMENT 2

The second experiment seeks to build on the results of experiment 1. There are three goals. First, to test whether the previous results are indeed an artifact of its design as just explained. Second, to test the robustness of the model and third, to introduce attribute evaluability as a variable that potentially modifies the performance of the model. The rationale for introducing evaluability is that easy-to-evaluate attributes are potentially less range sensitive to people's categorization judgments, and this in turn affects the model's performance. Consumers face both types of attributes and therefore it is relevant to study whether evaluability influences the performance of the CU model.

Method

The task: Participants were asked to answer the same task used in experiment 1. They were shown several ranges of attribute values and they had to issue membership judgments for each value within the ranges. The differences with respect to experiment 1 are related to the way information was presented to participants. Those differences are detailed in the following paragraphs.

To address the concern about false consistency of participant responses, a between subjects design was used. This way, participants produced membership judgments for only one side of the dichotomies (i.e., A or B). These judgments were afterwards matched and combined with other group's judgments to generate the CU estimations. If the model still performs well, the negative correlation between the average membership judgments of opposite categories should persist.

The robustness of the model was tested by extending the phenomenon to more ranges defined in a different way. Thus, three ranges were used this time where each was a subrange of a feasible wide range. These ranges were defined as follows: The wide range contains 25 values. Subrange 1 contains values from the 1st to the 15th , subrange 2 contains values from the 5th to the 20th, and subrange 3 contains values from the 10th to the 25th. This rule was adjusted to produce integer values for each range. This design tests the robustness of the model because it provides ranges that are closer to each other than those of Experiment 1. In addition, note that the ranges of experiment 2 have the same amplitude instead of common lower end point as those of Experiment 1. Finally, the distances between values within the ranges are the same across the three ranges.

To introduce attribute evaluability as a variable, 6 goods were chosen such that three were represented by continuous attributes of product/services that are easy to understand and evaluate for lay people and the other three were difficult to evaluate unless participants had some experience using the product/services. Appendix 3 summarizes the products, attributes and ranges.

Participants were allocated at random to 6 groups. Table 2 summarizes the treatments. Each participant issued membership judgments for the 6 attributes, (3 easy and 3 hard). Each participant issued judgments for only one (out of 3) range per attribute, and for one side of the dichotomy (A or B) per range. Note that the numbers inside the table correspond to the range number. The experiment was programmed using the software ztree and was run in the laboratory. In this experiment, instead of asking directly for [0,1] estimates, a slide bar was presented on the computer screen with end points “it doesn’t belong to the category at all” and “it totally belongs to the category” and people were asked to place the cursor along the slide bar. The computer automatically coded their answers on the [0,1] interval.

Participants: Experiment 2 was undertaken with 88 participants recruited on campus. They were paid a flat fee of 6 euros for participating.

Table 2. Experimental design and treatments for experiment 2.

		Easy			Hard		
Group	Category	*Attribute 1*	*Attribute 2*	*Attribute 3*	*Attribute 4*	*Attribute 5*	*Attribute 6*
1	A	1	3	2	3	2	1
2	A	2	1	3	2	1	3
3	A	3	2	1	1	3	2
4	B	1	3	2	3	2	1
5	B	2	1	3	2	1	3
6	B	3	2	1	1	3	2

Note: The numbers in the table correspond to the range number.

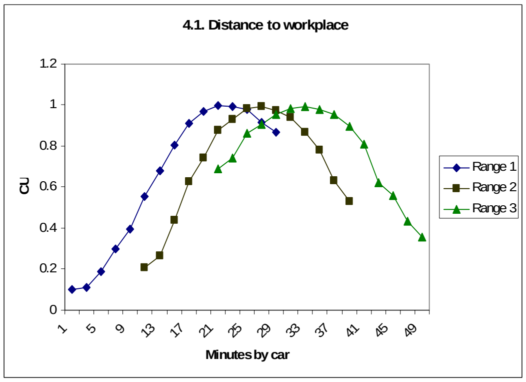
Results

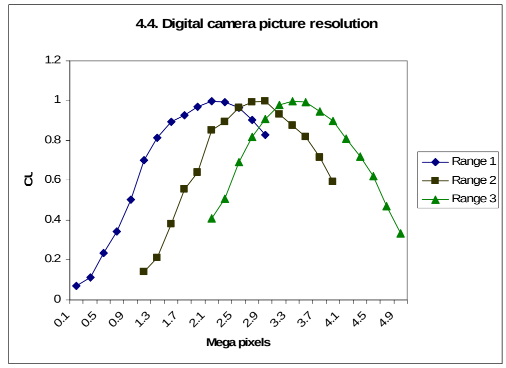
Figures 4.1 to 4.6 display the results.

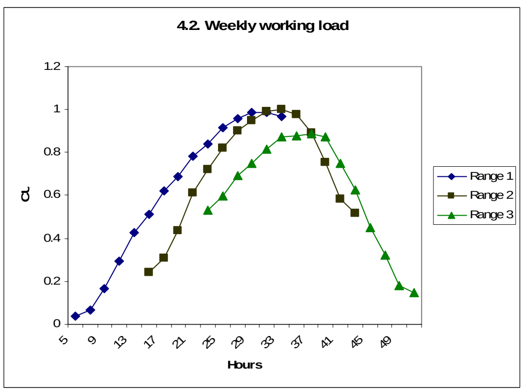
Figures 4.1 to 4.3 (Easy attributes) and 4.4 to 4.6 (difficult attributes)

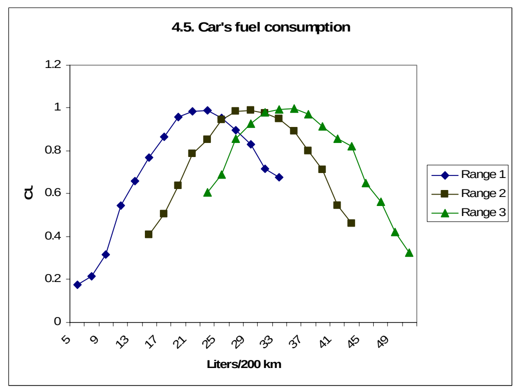
EASY ATTRIBUTES

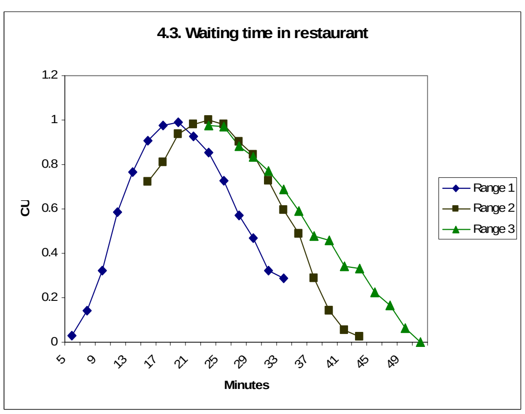
DIFFICULT ATTRIBUTES

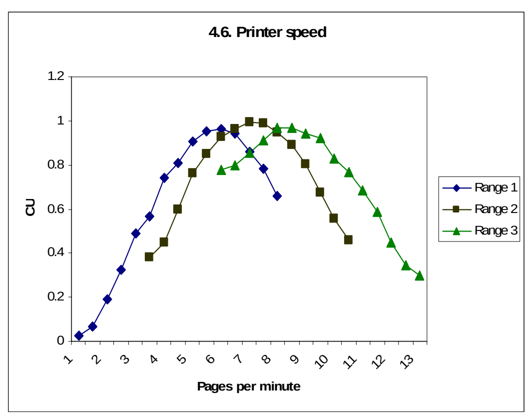












Confirmation of the results from experiment 1: Note first that the negative correlation of average membership judgments persisted between subjects causing the CU curves to maintain in most cases the expected bell shape. However, the lower levels of uncertainty at the end points of the curves are higher than those found in the first experiment. This may be due to the between subjects design and to the division of the hypothetical global range used. In experiment 1, range values were more extreme and more separated.

Robustness of the model: The effect of the three ranges design interacted with the use of easy and hard attributes. Note that the displacement of the CU curves along the ranges is very clear in figures 4.4. to 4.6, which correspond to hard attributes. This displacement is not that clear for the easy attributes (figures 4.1 to 4.3). For the hard attributes, the curves are almost repetitions of each other, centered around the mean of their respective range. This means that any attribute value *x* has a different probability of being categorized in one or another category as a function of the range in which it is embedded. Interestingly, in figures 4.1 to 4.3 where the easy attributes were plotted, the range effect is less powerful and the CU model does not perform as well, at least at the subranges. The curves for the easy attributes seem to be just part of a global CU curve that covers the wide range (in which the three subranges are contained). Note for instance that two of the CU curves fail to show a bell shape form. However, this means only that range sensitivity is weaker for easy attributes, but given the appropriately wide range, the CU model would predict the categorization judgments accurately.

These results show the limitations and the robustness of the model and may indicate that it is more powerful when applied to attributes that are somehow difficult for people because of technicalities or lack of familiarity. However, on global wide ranges the model seems to perform well also for familiar attributes. In addition, the applicability of the model is supported by the fact that current products and goods are increasingly complex and full of technical attributes whose global limits are difficult to identify. I will now move on to explore further the application of the model in the next experiment.

EXPERIMENT 3

Thus far, I have been exploring the theoretical properties of the model in settings where subjects did a kind of awkward task of categorizing numbers for a complete range of values. The practical worth of the CU model will become clear if it is able to predict the categorization of particular values within a more realistic evaluation context. This is the goal of experiment 3.

Method.

The task: I showed participants 6 pieces of advertising/announcements in which one or various attributes of the product are expressed quantitatively. Similarly to experiment 2, participants were asked to categorize that value as member of one side of a dichotomy using a slide bar with end points: “it doesn’t belong to the category at all” and “it totally belongs to the category”. The task was programmed using the ztree software. Once again, the computer automatically coded their answers as [0,1] membership judgments. I used the same goods/services and attributes of experiment 2 and the middle ranges of those defined also in experiment 2. It was a 2 x 2 design with the following characteristics.

The first manipulation consists of including or not in the ads, the range of reference for the attribute value. For example, the stimulus *with* range for fuel consumption is the following:

> The brand XXX has launched a new car. It features 4 airbags, temperature regulator and DVD player. Its fuel consumption is 29 liters per 200 kilometers. Cars within this category usually consume between 15 and 43 liters per 200 kilometers.
>
> Please, using the slide bar, indicate to what extent you think this is an "efficient" car in its fuel consumption
>
> *It doesn't belong to the category at all ---------------------------------- it totally belongs to the category*

The stimulus *without* the range was exactly the same except that it lacked specification of the range information.

The other manipulation corresponds to the uncertainty level of the attribute value to be categorized. A high uncertainty value is the one located on the mean of the chosen range, regardless of the range being disclosed or not. Similarly, a low uncertainty value lies close to one of the extremes of the range. In this experiment, for the low uncertainty values I used the "positive" side of the ranges (i.e., "efficient", "close", etc) Therefore, attribute values were chosen such that, according to the corresponding CU curve, they lie either near the 50% of the distribution, which is the point of maximum uncertainty, or at the 10% - 90% of the distribution which is the low uncertainty area. CU's were calculated as cumulative normal distributions using the range parameters (mean and standard deviation). Note that the probabilistic interpretation of the CU curve that allows us to predict that, for instance, value *x* will be categorized as "close" by a certain percentage of people. This yields four groups displayed in table 3.

Table 3. Experimental design of experiment 3

	Without range displayed	**With range displayed**
High uncertainty values	1. High predictability	2. High predictability
Low uncertainty values	3. Low predictability	4. High predictability

The table should be understood in the following way:

Group 1 – *Without range, High uncertainty value*. The expected predictability of the average membership judgments in this group is high, because the CU model predicts values around 50% of membership (meaning random membership) and therefore that is what we expect from people.

Group 2 – *With range, High uncertainty value.* The expected predictability of this group is also high, because despite the presence of the range, the categorized value is in the middle of the range, therefore, membership judgments will be predicted again near the 50%. However, the effect of the range could lead to people to be more consistent around the 50%, hence reducing the variance of categorization judgments.

Group 3 – *Without range, Low uncertainty value*. The expected predictability of this group is low. The absence of the range should make people issue membership judgments more randomly, whereas the CU predictions are values on either the 90% or the 10% membership probability, depending on the category.

Group 4 – With range, low uncertainty value. The expected predictability of this group is high. The range effect should make people issue judgments closer to the 90% or 10% membership probability according to the CU predictions.

Participants: 58 undergraduate students recruited on campus at UPF completed the task. They were divided randomly in four groups according to the four groups of the experimental design. They responded to three ads in the low uncertainty scenario and three in the high uncertainty scenario. They received a flat fee of 5 euros for their participation.

Results

The outcome of experiment 3 is close to expectations. Groups one and two displayed good levels of predictability, with a small increase for group two, where values were indeed slightly closer to the 50% membership. Group three displayed the poorest predictability according to expectations. There was a marked improvement in predictability for group four, for which membership judgments clearly abandoned the 50% area and moved to the extremes. This was precisely the expected effect of including the range in the ad. Results are summarized in table 4.

Table 4. Results of experiment 3. Estimated average membership judgments and actual membership judgments.

	Without range			**With range**		
High uncertainty (middle range values)	Group 1. high predictability			Group 2. high predictability		
	Real	Estimated	Differences	Real	Estimated	Differences
Close (minutes by car)	0.53	0.50	0.03	0.45	0.50	0.05
Reduced (working load)	0.41	0.41	0.00	0.44	0.41	0.03
Fast (waiting time at a rest)	0.29	0.59	0.30	0.35	0.59	0.24
High (digital camera´s pic. resolution)	0.65	0.50	0.15	0.50	0.50	0.00
Efficient (car´s fuel consumption)	0.46	0.50	0.04	0.49	0.50	0.01
Fast (printer´s speed)	0.56	0.50	0.06	0.65	0.50	0.15
Average difference			0.10			0.08
	Group 3. low predictability			Group 4. high predictability		
Low uncertainty (end range values)	Real	Estimated	Differences	Real	Estimated	Differences
Close (minutes by car)	0.91	0.92	0.01	0.89	0.92	0.02
Reduced (working load)	0.67	0.88	0.20	0.87	0.88	0.00
Fast (waiting time at a rest)	0.54	0.92	0.37	0.85	0.92	0.07
High (digital camera´s pic. resolution)	0.11	0.08	0.03	0.24	0.08	0.16
Efficient (car´s fuel consumption)	0.55	0.92	0.36	0.69	0.92	0.23
Fast (printer´s speed)	0.33	0.08	0.24	0.29	0.08	0.20
Average difference			0.20			0.12

Overall, for the three high predictability groups the model performed well, Surprisingly, the low predictability group was not as bad because of good predictions for two of the four attributes. This implies that (1) the CU model can predict some directionality in the categorization judgments of attributes in situations of low predictability, pointing accurately whether the probability of being categorized is low (below 50%) or high (above 50%). (2) When the ranges are communicated to people, the assumptions of the CU model exert a significant effect on people's membership judgments, generating reasonably accurate predictions of the probability of categorization. These results imply that a simple tool, like including the ranges in the communication of quantitative attributes, increase the predictability of the meaning that people derive from such information, giving marketers new tools as will be further explored in the discussion section.

DISCUSSION

This research shows that the categorization of quantitative attributes in dichotomous categories can be modeled and accurately predicted under the assumption of fuzzy categories and range sensitivity. As the literature suggests, judgments at the attribute level are highly important for people understanding and evaluating the meaning of decision attributes (Viswanathan and Childers, 1999). The categorization literature, however, has mainly focused on how people assign objects to categories and which types of categorization processes occur as a function of different personal and contextual variables. Most categorization processes described in the literature are based on similarity judgments. Some are related, for instance, to object similarity in taxonomic and goal derived categories[6] (e.g., Felcher, Malaviya and McGill, 2001). Others describe similarity judgments to be made on analytic (attribute-by-attribute) and non- analytic (holistic comparison) information retrieval strategies of exemplars (Basu, 1993; Cohen and Basu,

[6] Taxonomic categories refer to objects that share physical features (e.g., dog, cars, computers), while goal based categories are referred to objects that serve the same purpose (e.g., cars, trains and airplanes for transportation)

2001). More sophisticated methods of categorization are attributed to causal relationships between category features, in which category membership is granted to an object if it was generated by the causal mechanisms that people associate to the category (Rehder, 2003). All those processes, however, require some understanding of objects at the attribute level. This work contributes to the categorization literature by providing insights on the categorization process at the attribute level, emphasizing instances where such process become more salient, like when consumers evaluate particularly complex products (e.g., cars, mobile phones, houses, etc) for which quantitative attributes are regularly disclosed. The importance of the present work lies in the fact that people's need for understanding quantitative attributes often triggers the categorization of quantitative information.

Categorization at the attribute level may also be a normal process to determine the extent to which the features of an object match the decision-maker's goals (e.g., if one wants a big house, then one needs to know whether the house under evaluation is big or not). This attribute-goal comparison is a requirement to select choice sets, such that the alternatives included in the set meet the decision goals to different extents. The argument is then, that what people do in order to obtain a helpful, goal-oriented choice set, is to produce judgments over the attributes and then use that information to make further comparisons among alternatives. For example, when buying a car, a person may define that she wants a fast, comfortable, reliable and economic car. Ideally, she must have a judgment over all these dimensions, for each alternative. Therefore, when making a decision over which car to buy, people will determine not just a set of cars, but a set of fast, comfortable, reliable and economic cars, for which any decision strategy can be used (e.g., compensatory, non-compensatory, etc). Following this idea, choice sets determined in the absence of attribute categorization may contain irrelevant alternatives (in terms of how they meet goals). Such choice sets are probably less efficient and lead to lower quality decisions. The CU model provides a tool to understand such attribute categorization and to predict and influence the membership judgments of consumers.The present findings suggest that instead of processing numbers directly people would rather find a way to understand the quantitative information by assigning category membership using increasingly the ranges they observe, as the attribute is less familiar or more complex. It could be considered, that the ideal starting point for people to understand quantitative information would be to have “absolute” quantitative ideas of what is fast, big, hard, etc for each context. One would expect that at least for some daily decisions, people might have such absolute quantitative references. However, the strong regularities and systematic biases found in the categorization judgments imply that people rarely store such absolutes in memory.

From a marketing perspective, the results presented here are useful for advertising strategies, product presentation and product design. They imply that when the quantitative attributes of a product are disclosed to the consumer, it is important to make sure that she categorizes the attribute as the marketer intends. For example, if the size of a new mobile phone is expected to be a salient attribute (offering an advantage over other options in the market), making the range of available sizes evident to the consumer during the advertising campaign will ensure the effective communication of such an advantage through the appropriate categorization of that attribute. This is a better strategy than trusting the consumer’s knowledge of the market and her ability to do a comprehensive screening of the available options (i.e., it is difficult and costly for consumers to figure out the sizes of the mobiles on their choice set). Disclosing the range may even prevent consumers from relying on other informational retrieval strategies of a more heuristic nature, framing them better to analyze attribute information objectively. Note also, that to prove the effectiveness of the model, I pushed the range sensitivity principle by modifying the categorization judgments within subranges of a wide feasible range. In real settings, marketers just need to uncover the wide feasible range and work over it, which should increase the predictive power of the CU model, giving the range sensitivity the simple role of provide an appropriate context for the consumer categorization process.

Other applications are feasible from the product design perspective, when making decisions about the attributes of a new product, (e.g., what should be the size of the new mobile such that consumers think it is small?). Knowing the range of values available in the market, combined with the high predictability of consumers' judgments, produces a specific approximation of the correct attribute value the product should possess, reducing in the process marketing research costs and even R & D costs.

In conclusion, the predictability and regularity of the categorization judgments over quantitative attributes found in the present work constitutes an insight into the psychological process of multiattribute choice, and therefore a useful tool for marketers in order to strengthen communication strategies and improve their decision making on product design. The present findings provide some insights into how people understand attributes and make sense of quantitative information, which are salient processes of product categorization and more generally for the evaluation of choice alternatives.

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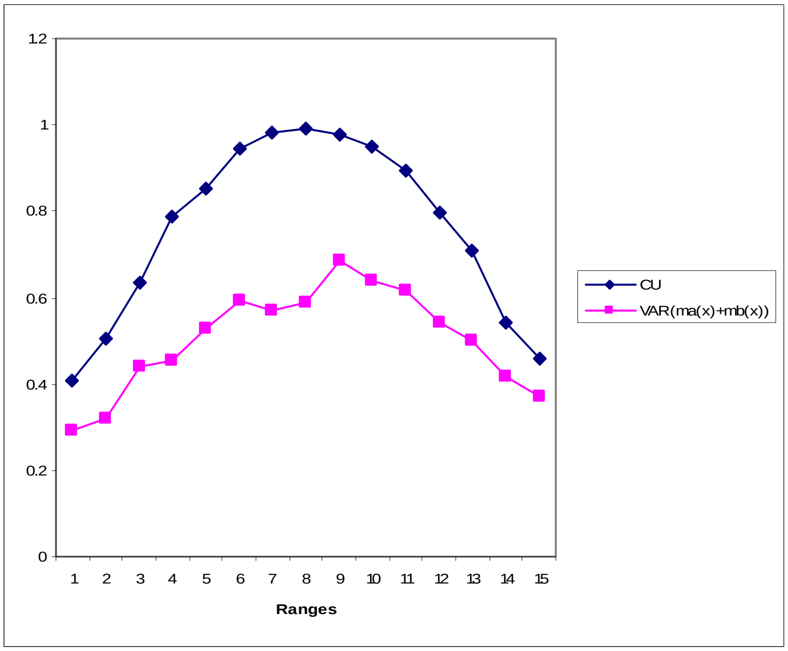
Appendix 1

Comparison of aggregated CU and $\mathrm{var}(m_A(x) + m_B(x))$



To obtain the curve of variances, the result of the variance calculation had to be multiplied by 4 in order to be comparable to the CU calculated from the same values (this is the curve of the middle range of fuel consumption from experiment 2). The variance generates an mathematically intractable function but the most important issue, is that the uncertainty captured by the variance is related to the variability of group responses, while the CU is the result of the inherent categorization uncertainty at the individual level (see figure above), which is the target psychological construct of the CU model, and the phenomenon that this paper is studying.

Appendix 2

Scales, Ranges and dichotomies of experiment 1

Weight (Kilograms)		Battery duration (Hours)		Job location (minutes by metro)		Training (percentage of working hours)	
Categories Light - heavy		Categories Durable -little duration		Categories Near - far		Categories Intensive - scarce	
Range 1	Range 2	Range 1	Range 2	Range 1	Range 2	Range 1	Range 2
0.5	0.75	15	22.5	5	7.5	40%	20%
0.7	1.05	14	21	8	12	37%	19%
0.9	1.35	13	19.5	11	16.5	34%	17%
1.1	1.65	12	18	14	21	31%	16%
1.3	1.95	11	16.5	17	25.5	28%	14%
1.5	2.25	10	15	20	30	25%	13%
1.7	2.55	9	13.5	23	34.5	22%	11%
1.9	2.85	8	12	26	39	19%	10%
2.1	3.15	7	10.5	29	43.5	16%	8%
2.3	3.45	6	9	32	48	13%	7%
2.5	3.75	5	7.5	35	52.5	10%	5%
2.7	4.05	4	6	38	57	7%	4%
2.9	4.35	3	4.5	41	61.5	4%	2%
3.1	4.65	2	3	44	66	1%	1%
3.3	4.95	1	1.5	47	70.5	0.50%	0%

Appendix 3. Attributes, ranges and categories for experiment 2

Easy attributes

Minutes by car to go to work			Weekly working load (hours)			Waiting time in restaurant (minutes)		
Categories			Categories			Categories		
Close - Far			Elevated - Reduced			Long - Short		
Range 1	Range 2	Range 3	Range 1	Range 2	Range 3	Range 1	Range 2	Range 3
1	11	21	5	15	23	5	15	23
3	13	23	7	17	25	7	17	25
5	15	25	9	19	27	9	19	27
7	17	27	11	21	29	11	21	29
9	19	29	13	23	31	13	23	31
11	21	31	15	25	33	15	25	33
13	23	33	17	27	35	17	27	35
15	25	35	19	29	37	19	29	37
17	27	37	21	31	39	21	31	39
19	29	39	23	33	41	23	33	41
21	31	41	25	35	43	25	35	43
23	33	43	27	37	45	27	37	45
25	35	45	29	39	47	29	39	47
27	37	47	31	41	49	31	41	49
29	39	49	33	43	51	33	43	51

Hard attributes

Digital camera's mega pixels			Car's fuel consumption (liters/200km)			Printer's speed (pages/minute)		
Categories			Categories			Categories		
Resolution high -Low			Efficient - Inefficient			Fast - Slow		
Range 1	Range 2	Range 3	Range 1	Range 2	Range 3	Range 1	Range 2	Range 3
0.1	1.1	2.1	5	15	23	1	3.5	6
0.3	1.3	2.3	7	17	25	1.5	4	6.5
0.5	1.5	2.5	9	19	27	2	4.5	7
0.7	1.7	2.7	11	21	29	2.5	5	7.5
0.9	1.9	2.9	13	23	31	3	5.5	8
1.1	2.1	3.1	15	25	33	3.5	6	8.5
1.3	2.3	3.3	17	27	35	4	6.5	9
1.5	2.5	3.5	19	29	37	4.5	7	9.5
1.7	2.7	3.7	21	31	39	5	7.5	10
1.9	2.9	3.9	23	33	41	5.5	8	10.5
2.1	3.1	4.1	25	35	43	6	8.5	11
2.3	3.3	4.3	27	37	45	6.5	9	11.5
2.5	3.5	4.5	29	39	47	7	9.5	12
2.7	3.7	4.7	31	41	49	7.5	10	12.5
2.9	3.9	4.9	33	43	51	8	10.5	13

Chapter 2:

Emotions, weights and categorical information in the determination of preferences.

INTRODUCTION

The role of emotions in judgments and choice is a focus of growing interest of research in decision making (Peters, Vastfjall, Garling and Slovic, 2006). The notion that affective reactions cause disturbances in rational processes and suboptimal decisions (Elster, 1998) is now constantly challenged as new integrative approaches of thought take reason and affect as necessary elements of the decision making process (Damasio, 1994). Following Damasio's path, several researchers have embarked on investigating the way in which emotions affect decisions. Even some previous "cognitive" findings of decision research are now reinterpreted in terms of their affective component (Slovic, Finucane, Peters and McGregor, 2002). So far, different approaches have been taken to explore the role of emotions. Some have focused on particularities of the role of affect, like the influence of anticipatory feelings in choice, the affective traits of individuals, or how affect can act as information for the decision maker. These streams of research shed light on what we can call different *moments* during the decision process at which emotions occur, but they fall short in explaining the general properties of the interaction of reason and affect.

Other lines of research take a broader approach, studying the interplay of reason and affect in the context of how the two types of information are integrated and accessed psychologically and neurologically. These approaches are highly informative regarding how cognition and affect interact during thought processes. However, these pieces of research do not provide an explanation of what happens with the cognitive and affective pieces of information at the higher levels of thought, where the evaluation of alternatives and decisions are finally made. Thus, we lack an explanation of how such processes of integration and interaction actually exert an effect in the way preferences are constructed.

On one hand, the literature contains detailed but scattered accounts of the role of affect in decisions, and, on the other hand, the general models of the interaction between affect and cognition are not clearly related to the construction of preferences. In this work, I attempt to close this gap by, first, proposing and testing four general models of choice based on different assumptions about the way cognitive-affective information is used while making decisions. Second, I propose a conceptualization of the role of affect in decision making according to (i) the moment during the decision process at which affective reactions occur and (ii) the nature of the affective reactions involved in such moments. It will be shown that the proposed models are good predictors of choice and that the variations in the way people's choice behavior is captured by the different models suggest some properties of how people let their emotions influence their preferences. In particular, people seem to develop what I call "procedural preferences" which I define as the control (conscious or unconscious) people exert on the way information and cues are utilized and mixed while making decisions. For the present work, I introduce the notion of procedural preferences in relation to the way cognitive and affective information is used. These procedural preferences help decision makers to exert a certain degree of control over information processing.

The chapter continues as follows. I first specify my research questions and proposals in greater detail as well as their contribution over the extant literature. Then I explain and develop the four models, which characterize the choice process according to four different possibilities of the way cognitions and emotions can interact. These possibilities range from mostly cognitive to mostly emotional. After that I present experimental work exploring the behavior of the models. The first experiment is devoted to testing the assumptions of the models regarding (1) the relation between cognition and emotion and (2) the effects of cognition and emotion on choice. The second experiment seeks to validate and extend the results of the first one, and to test directly the predictive power of the models by (a) fitting them to individual choices and (b) introducing the depletion of cognitive resources as an influencing factor in the way the models capture people's behavior. Continuing, I explain the results and propose the moment-based conceptualization of affect in decision making and further discuss the experimental results using this framework. Finally I close with a general conclusion and research agenda.

BACKGROUND

Emotions and Decisions

The roles of emotions in decision making are multiple and complex. Researchers have explored different aspects of this question, but the results obtained so far are scattered. Some researchers have paid attention to the emotional state of the individual. For example, good mood has been related to faster and more efficient decision making (Isen, 1993, 2001). Anger and sadness affect the way in which people make causal attributions (Keltner, Ellsworth and Edwards, 1993) and personality factors also may have an effect on how responsive people are to emotionally loaded information (Peters and Slovic, 2000). This way, according to past research, people are affected by their emotions in ways they are not necessarily aware of, but that later on will determine, to some extent, how alternatives are evaluated. However, these results provide no particular insight on whether the expressed preference would be actually influenced or directed by the emotional state. The main effects described by these works are related to the way information processing is influenced by emotions, but there is no indication on whether these processing differences translate into various types of emotionally determined preferences.

Other work has focused on how specific emotions are triggered by the target (Pham et al., 2001). These are vivid emotions than can serve as information about preferences (Gorn, Pham and Sin, 2001; Schwarz and Clore, 1996). This is known as the affect-as-information approach, according to which affective reactions are used as judgmental information at the moment they are experienced during the decision process (Pham, Cohen, Pracejus, and Hughes, 2001) It is not clear, however, how these affective reactions interact with cognitive evaluations. For instance, emotions are considered to be generated faster, to show a higher level of inter-participant agreement and to predict better the valence of thoughts towards the decision target (Pham et al., 2001). But other emotions are the result of the cognitive appraisal of the information (Lazarus, 1991) as well as the outcome of meta cognitive experiences (Schwarz, 2004).

In the same line, it has been found that people not only react affectively to the information they see, but they also try to cope with meta-emotions related with the process itself, like the difficulty of performing trade-offs (Luce, Payne and Bettman, 1997, 2000, 2001). In addition, the way some information is evaluated may depend on the extent to which people rely on feelings (Hsee and Rottenstreich, 2004). This way, as noted by Pham (2004), there is a wide range of inferences that are made from momentary feelings and, more importantly, reliance on affective information is beyond the mere effort-minimizing, peripheral judgment strategy usually attributed to emotional evaluations. Feelings are also invoked selectively while the choice prospects are evaluated, and people assess the ecological validity of emotional cues (Pham, 2004). Such assessments are constructed while choice actually occurs and therefore the interaction of affect and reason is critical for the outcome of the decision process. These ideas are the source of the notion of procedural preferences I use during this chapter.

There are also research efforts (notably from economists) on the role of anticipatory deliberations about particular post-decision feelings like regret, guilt, disappointment or enjoyment and realization (Elster, 1998) According to this approach, people modify their preferences trying to anticipate what they will feel after choosing, and therefore minimizing the expected negative feelings or maximizing the positive ones. Some choice models are based on these anticipations (Mellers, Schwartz and Ritov, 1999: Mellers, 2000). However, such models need a friendly environment that provides accurate feedback (Hogarth, 2001). These feelings may lead people to seek confirmatory evidence for their choice in order to avoid cognitive dissonance and unpleasant feelings. In addition, the level of surprise as well as overconfidence in the outcomes influences satisfaction or disappointment (Mellers at al. 1999; McGraw, Mellers and Ritov 2004). However, anticipatory judgments are only relevant to models of choice as long as people employ strategies during the construction of preferences to maximize the net feelings of pleasure in the post-choice situation and there is no specific account of how such feelings interact with others of a different nature (i.e. emotional states, meta-emotions, etc)

Peters (2006) has conceptualized different "roles" of affect in the construction of preferences. First, affective information has informational value, as described previously. Second, affect serves as a spotlight focusing people on certain information according to the intensity and valence of such feelings. Third, Peters remarks that affect is a motivator of behavior; and fourth, affect helps to make comparable different types of information by "translating more complex thoughts into simpler affective evaluations" (Peters, 2006, pp.

8). Note that Peters's work provides insights into the instrumental value of affect for decision makers but not on the affective component of the preferences, which is the question raised here. In that respect, the literature acknowledges certain stages of very high emotional arousal in which people behave totally driven by intense emotional states, which are part of visceral factors (Loewenstein, 1996). These are stages related to hunger, psychopathological situations or addictions that are outside the threshold of normal decision making processes where people are capable of using their cognitive and rational capabilities. Visceral factors are not of interest in this work.

In summary, past research on affect and emotions has produced interesting insights on how they alter the way in which people evaluate information, but it is not easy to infer from all this work a general notion of how, and to what extent such emotions and emotionally determined judgments actually determine preferences. This represents an important question for decision making researchers that I attempt to start answering in the present work.

Interplay of reason and affect

Research on affective reactions leaves the impression that cognitive and emotional valuations of alternatives happen at the same time, and even if some emotions are highly accessible and fast, others require longer evaluations[7] (e.g., coping with the difficulty of trade offs). Therefore, only some emotions are part of an experiential system; those acquired by conditioning. Other types of emotions may interact differently with cognitive evaluations and may belong to other systems of thought. For instance, the emotions

[7] Pham (2004) defines three types of emotions according to the evaluation they need. Type I are primary and bio-regulated, type II are affected through conditioning (like the fear a tough professors causes) and type III are controlled appraisals of stimuli. (p. 365)

controlled biologically require little conscious deliberation and are attached to adaptive and fast mechanisms (e.g., the fear triggered by a tiger). Contrastingly, emotions triggered by cognitive appraisals (e.g., the pleasure of earning profits in the stock market) belong to a deliberative system. We need therefore to disentangle the mixed effects of emotions and reasons and look for some general principles of cognition and feeling during the construction of preferences.

For some time there has been a debate about how independent cognition and affect are, in the decision making process. Zajonc (1980) was in favor of cognition and emotion as two independent systems while Lazarus (1992) reckons that some prior cognition is necessary to generate an emotional response. Subsequent research has inclined the debate towards a cognitive-affective processing of stimuli over the independence hypothesis (Anand, Holbrook and Stephens, 1988). It has been found, for instance, that cognition and affect are salient constituents of attitudes that operate together (Verplanken, Hofstee and Janssen, 1998), and that the inclusion of emotions as predictors of behaviors in attitudinal models increases the predictive power of such models (Allen, Machleit and Kleine, 1992). A recent cognitive model of attitude formation and choice found that the interaction between cognition and emotion is significant, while a direct effect of cognition or emotion is not as salient (Agarwal and Malhotra, 2005).

There has also been intensive research on the underlying psychological and neurological processes that link cognition and emotion. Damasio (1994) and Bechara and Damasio (2005) developed and provided neurological evidence of their "Somatic Marker Hypothesis" according to which a cognitive-emotional assessment of a stimulus is associated with certain outcomes and stored in memory. When a similar stimulus is recognized, the somatic marker is activated and the previously stored affective response is triggered. This supports the idea of a cognitive-affective process that enters the decision making process. Cognition and affect are also found to be integrated during decision making through the activation of certain areas of the brain that recognize both the affective and the cognitive responses to stimuli as well as the context in which the stimuli are embedded. If there is consistency between both the context and the cognitive-affective responses to the stimulus, the two are integrated and passed to the higher levels of reason where analysis of the decision takes place (Wagard and Thagard, 2004).

In summary, the literature suggests that cognition and affect are integrated and the combined information is then used in higher level processing, responsible for the formation of attitudes and preferences. These models, however, don't provide insights into what people actually do with this information once it has reached the higher levels of thought, where most decisions are actually made. We need therefore a range of models that make operational the use of cognitive-affective information during the construction of preferences thereby answering how and when people use the complex combination of cognitive-affective information.

THE MODELS

The models of choice that are developed here are based on two ideas derived from the literature. First, there is an interdependence of cognition and affect in the formation of preferences. Second, affective information, irrespectively of its source (e.g., mood, anticipation, etc.), is somehow integrated into a holistic affective evaluation of the attributes and alternatives. This integration of cognitive and affective information raises new questions regarding the way people incorporate such “bundles” of information into their choice process.

To elaborate a simple model of such a process with the above mentioned characteristics, cognitions and emotions must be captured by unique elements in the models. I develop a series of models that are, to a great extent, modified versions of a standard Multiattribute Utility Model (MAUT) (e.g., Keeney and Raiffa, 1976). This way, I consider models of a choice task where people choose the alternative with the highest utility. Each alternative is composed of different attributes. In this work, I consider only binary choices (i.e., choices between two alternatives, A and B). In addition, each alternative has only two attributes.

To characterize the unique elements of cognitions and emotions in such a model, I summarize the cognitive judgment over an alternative in the weights (*w*) given to the different attributes. In weights, arguably, people convey their knowledge about the target, their goals and their experience in similar situations. Weights should be considered local evaluations of relative importance of the attributes (Goldstein, 1990) provided that participants have a well defined decision problem. On the other hand, the emotional reactions conveyed by the attributes will be modeled as a measurable holistic emotional appreciation (*e*) about the attributes of the alternative.

With all the elements just described, consider the following multiattribute models of choice. For all models the value (utility) of an alternative A_j is described by a vector of n attributes x_i. An emotional reaction to attribute x_i is given by e_i and the weight of attribute x_i is given by w_i. The purpose of proposing different models is to capture the notion that people are able to monitor the cognitive-affective information they receive from their brains as well as to determine the way in which such information will be processed. They may choose to use a decision strategy that ranges from more cognitively to more emotionally loaded.[8] I will therefore consider four models that lie in that range. The two intermediate models vary in the way cognitive and emotional information is integrated. All models have an additive structure.

Model 1, ACC (Additive, Compensatory, Cognitive)

In this model, cognitive evaluations are the main mechanism to determine a preference, meaning that people will prefer to rely heavily on cognitive information (i.e., past experience, knowledge, etc.). The cognitive-affective information has a low instrumental value. This situation can be captured by a classical compensatory multiattribute utility model in the spirit of Keeney and Raiffa (1976) such that

$$A_j = \sum_{i=1}^{n} w_{ij} x_{ij} \tag{1}$$

Model 2, ACcE (Additive, Compensatory with correlated Emotions)

In this model cognitions and affect interact such that the emotional reactions depend on the cognitive weight assigned to the attributes (e.g., if the most important attribute of a car is its speed and the car considered is a *fast* one, the emotional reaction is stronger than that of a person who does not consider speed important) and the total weight of the attribute would be the sum of the purely cognitive w_i^c and the incremental affective weight $e_i = w_{ij}^e(w_{ij}^c)$.

Note that the cognitive-affective information is modelled as if cognition precedes emotion

[8] Such procedural consideration may be conscious or unconscious but this distinction is not under the scope of the present work.

and the affective load of an attribute is a function of its cognitively determined weight. It should be noted that the participant is probably unable to separate the cognitive and the affective part of the subjective weight. This can be captured by a compensatory model with correlated cognitions and emotions such that:

$$A_j = \sum_{i=1}^{n} \left[w_{ij}^{c} + w_{ij}^{e}(w_{ij}^{c}) \right] x_{ij} \qquad (2)$$

Model 3, ACncE (Additive, Compensatory with non correlated Emotions)

In this model there is no assumption on whether cognition precedes emotion or the opposite. I assume an integration process in which they are combined equally to produce a total cognitive-affective evaluation of the alternative. This means that people may allow for some purely cognitive or purely affective information. This can be a compensatory model where cognitive weights and emotions are uncorrelated. The holistic emotion is a function of the combination of attribute values.

$$A_j = \sum_{i=1}^{n} w_{ij}^{c} x_{ij} + e_j(x_{ij}) \qquad (3)$$

Model 4, E (Emotional)

In this model people rely heavily on the affective component of information disregarding cognitive considerations. This situation can be captured by a non-compensatory model where the value of the alternative is directly determined from the net affective reactions to the attributes. This model leaves open the possibility that people perform compensatory operations among emotions, therefore the non-compensatory nature of the model is considered across the cognitive-affective combination of information.

$$A_j = \sum_{i=1}^{n} e_{ij}(x_{ij}) \tag{4}$$

Note that all terms in the models are subindexed with *j*, meaning that the cognitive-affective judgmental information depends on the alternatives under evaluation. This captures the idea of context variability and local generation of judgments. This means that the same attribute value can be weighted differently or produce a different affective reaction when embedded within a different set of alternatives.

EXPERIMENT 1

The first experiment is aimed at testing the general properties and assumptions of the models. These are, first, the level of correlation between affect and cognition. The literature suggests that these two psychological activities operate interdependently. The models proposed try to capture this relationship. In particular models ACcC and ACncE capture two possible forms of their relation. In model ACcE the affective reactions are a function of cognitive weights and in model ACncE affect and cognitive weights are independent. These are the two extreme possibilities of the relationship between cognition and emotion. Meanwhile, models ACC and E are purely cognitive and purely emotional respectively and therefore they do not require an assumption on the relationship of cognition and emotion.

Second, it is necessary to test the significance of the effect of both affective and cognitive local judgments in choices. The models are based on the idea that people use cognitive and affective information in the construction of preferences and, therefore, the statistical significance of the two on the probability of choice is a necessary check in order to assess the validity of the models.

These two properties of cognition and emotion (i.e., relation and effect on choice) provide elements to evaluate which model(s) is (are) more appropriate to capture the use of cognitive-affective information in choice. Since the basic premise of this research, as mentioned before, is that emotions and cognitions influence preference construction interdependently, the following hypotheses are formulated.

H1: There is a significant relationship between cognitive weights and affective reactions.

H2: Both cognitive weights and affective reactions have a significant effect on the probability of choosing a given alternative.

Method

The task: The models are tested using a simple task in which participants make a series of 12 binary choices (i.e., choosing between alternative *A* and alternative *B*) over different types of consumption goods and services. Each alternative is described by only two attributes (*x* and *y*)[9] and each alternative is better than the other on one of the attributes.

[9] See appendix 1 for the list of decision objects and their attributes.

Option A $\begin{cases} x_A \\ y_A \end{cases}$ Option B $\begin{cases} x_B \\ y_B \end{cases}$ where $x_A \succ x_B$ and $y_B \succ y_A$.

Manipulations and treatments: To allow for a wider range of affective reactions and enrich the study, I use the notion that numerical information may be too "cold" and therefore I introduce some attributes expressed verbally expecting them to produce more "vivid" emotional reactions. In addition, dealing with numerical and verbal information may trigger different cognitive processes in people, with direct consequences in the ways trade offs are performed (i.e., trading off two quantities is different than trading off a quantity and a verbal expression like "slow"). The idea is to introduce one verbal attribute in one of the alternatives in order to induce these effects. This way, several treatments can be employed. Following is a detailed description of these treatments and the research questions behind them (see table 1)

1. Verbal-Numerical manipulation: The information of the attributes is expressed mostly in numbers, but in some treatments one alternative will contain one attribute expressed verbally (e.g., long, fast, near, etc). As mentioned above, the purpose of this manipulation is twofold. First, verbal information may help to infuse affective content in attribute information (Slovic et al, 2002, Damasio, 1994). Second, including one verbal attribute may modify the way tradeoffs are performed. I explore the idea that trading off two quantities imposes a different cognitive and affective load than that of trading off a quantity for a verbal concept. This,

potentially changes the meta cognitive component of the affective evaluations and therefore preferences may be affected. The verbal presentation is counterbalanced.

2. Positive-Negative: This manipulation follows the first one. The attributes that are expressed verbally may refer to the superior (positive) attribute of an alternative or to the inferior (negative) (e.g., near or far, fast or slow). The literature (e.g., Isen, 1993) contains accounts of asymmetric effects of positive and negative feelings in information processing. This way, if verbal information elicits a more intensive affective response, the valence of such a response may exert a differential effect in choice.

3. Selective measurement of emotions: Affective responses are measured to accomplish two goals: first, to provide a measure of emotions that can be used in the analysis of the two hypotheses; second, to check whether the verbal-numerical treatment has an effect and therefore whether verbal attributes cause a stronger emotional reaction. Such measurement is performed towards alternative *A* or *B*, such that I can compare the affective responses to alternatives when they contain a verbally expressed attribute and when they do not. For instance, one group of participants chooses between A and B when option A contains a verbally expressed attribute and affective responses to A are recorded. Another group makes the same choice but all attributes are expressed numerically and affective responses to A are recorded. I proceed similarly for option B.

These manipulations and selective measurements of emotions provide six different treatments that are summarized in Table 1.The columns in Table 1 correspond to the attribute that is expressed verbally (e.g., the good attribute of A) The rows correspond to the selective measure of emotions (i.e., towards A or B). This way, the entries of the table show the treatments resulting from the combination of the two manipulations. For instance, treatment Verbal, A(+),A means (1) that decisions in that treatment contain a *Verbal* attribute, (2) that such attribute is the positive or “good” aspect of alternative A, (*A(+)*) and (3) that emotions towards alternative A were measured.

Table 1. Summary of treatments, and treatment names for experiment 1

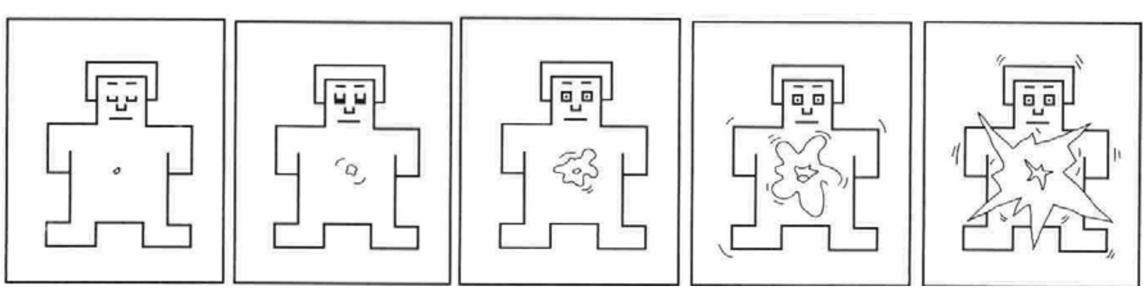
		Verbally expressed attributes				
		Good attribute of A [A(+)]	Good attrubute of B [B(+)]	Bad attribute of A [A(-)]	Bad attribute of B [B(-)]	All numerical
Measurement of emotions	Towards A	*Verbal,A(+),A*		*Verbal, A(-), A*		*Numerical A*
	Towards B		*Verbal,B(+), B*		*Varbal, B(-), B*	*Numerical B*

Measurement tools:

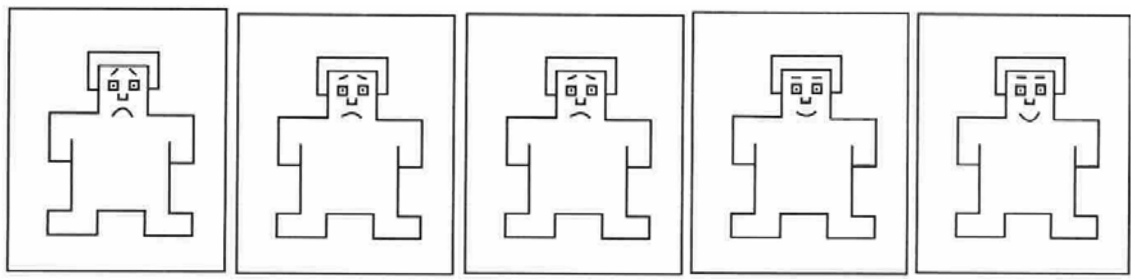
Emotions: Measuring emotions is a critical step in this research. It is necessary, in order to capture the emotional term of the models. To quantify emotions, some authors have used simple one-dimensional scales with opposite verbal end-points to measure self reported affective reactions. For example, Mellers et al. (1999) used a scale ranging from -50 (extremely disappointed) to 50 (extremely elated). Such a scale is inappropriate for this research because (1) elation and disappointment are arguably opposite feelings, and (2) verbalization and quantification of feelings may force a cognitive evaluation altering its true nature. Slovic et al. (2002) also describe studies where bad – good scales are used as affective measures. Those may also suffer the downsides just explained. Emotions are multidimensional reactions, very difficult to capture accurately by a verbal one-dimensional scale. Bradley and Lang (1994) developed a non-verbal method of measuring emotions based on the judgment of similarity between feelings and the expression on a simple drawing of a person, whose facial expressions indicate different emotional states. Using factor analysis, they show that emotions can be well captured by three dimensions, namely, arousal, valence and dominance. However, the first two are the most important and salient, as well as the ones that better correlate with other extensive instruments of affective measurement. The instrument is called S.A.M (Self Assessment Manikin) (see figure 2). Bradley and Lang have successfully used S.A.M to produce a quick measure of affective reactions to a wide variety of stimuli. Thus, I have chosen this instrument to measure participants' emotional reactions. Other objective ways to measure emotions, like the electric activity of the skin, were not considered. The reasons are its high cost and the complexity of isolating the "mild" physiological reaction triggered by stimuli used in the present work from other sources of emotions.

Figure 1. Example of S.A.M

Dimension 1: Arousal



Dimension 2: Valence



Participants could rate their feelings by placing an "X" over any of the drawings, or between drawings, in each dimension (i.e., arousal and valence). This way, the arousal dimension was coded from 1 to 9, and the valence dimension was coded from -4 to 5 (excluding 0). The two scores provide a two dimensional measurement of emotions. These dimensions can be used as two different variables, or could be plotted in an emotional "space" (see Bradley and Lang 1994). In the present work I translate the two dimensional plot into a single scale by multiplying the arousal and valence scores. The product of the two scales yields a broader bipolar scale, ranging from -36 to 45 (i.e., from highly aroused and unpleasant to highly aroused and pleasant) (See appendix 3 for further discussion on the determination and use of the multiplied scale).

Weights: The models capture the cognitive component of the decision process through the weights given to attributes (*w*), therefore, it is necessary to obtain the participant's weighting functions for each pair of attributes involved in the different decisions. In order to do so, I asked individuals to report at the end of the experiments, how they would distribute 100 units between every pair of attributes that were used during the study. Remember that the alternatives for each of the twelve decisions contained two attributes.

This way, there were twelve pairs of attributes, and participants rated the relative importance of these, within each pair.

Additional methodological details

All participants attended a pretest 2 weeks before the actual experiment. The purpose of this pretest was to make sure that at the individual level, the meaning conveyed by the numerical and the verbal representations of attribute was the same. For this objective, participants were asked to state the verbal-numerical equivalents of all the categories used. Therefore, each participant had a customized set of attribute values (e.g., if a participant said that a *fast* car is the one which reaches a maximum of 300 kilometers per hour, this is the information he observed if assigned to a numerical treatment).

The experiment was undertaken using a special web based software written to handle graphics and record answers. The S.A.M task and the choices were managed separately. That is, the emotions towards the alternatives were measured at a different moment during the experiment from that or the decision to which such reaction referred. The order of presentation of both decisions and emotional measures was randomized.This step was taken in order to avoid emotional responses from participants that were falsely consistent with choices due to their proximity. Asking for the emotional reports separately contributes to ensuring that the true emotional reaction is captured. Response times were also recorded in order to check whether the level of emotions related to a decision affects the time employed in that decision. Some authors have suggested that emotional decisions are faster than cognitive ones (e.g., Pham et al., 2001).

Participants: 68 people participated in the experiment, 24 business undergraduate students, 12 graduate students of finance, 19 of marketing and 13 business executives. They were recruited on campus, at CESA[10]. They received a flat fee of approximately five euros for their participation. This sample yielded a total of 816 choices to analyze.

Results

H1. Relation between weights and emotions

To analyze whether weights and emotional reactions were related, the responses to S.A.M were regressed on the weight of the (verbally) manipulated attribute for each treatment. This way, the dependent variable is the holistic affective reaction towards an alternative, and the independent variable is the weight given to one of its attributes. For instance, in treatment Verbal, A(+), A, the positive attribute of option A was presented verbally (i.e., manipulated) and emotions towards option A were measured. Thus, I can evaluate the predictive value of the weight assigned to the manipulated attribute in terms of the emotional reaction towards the option containing that attribute. This approach was taken in order to analyze not only the relationship of weights and emotions, but also whether there are differences in the emotional reactions as a result of the experimental manipulations.

In this experiment, we expected to find a relation between weights and affective reactions in each treatment. Recall that the rationale behind this relation is that the more important an attribute, the more intense is the emotional reaction towards it. This way, in treatments Verbal, A(+), A and Verbal, B(+), B the positive attribute is manipulated and therefore the relation should be positive. Treatments Numerical A and Numerical B are purely numerical, meaning that no attribute is expressed verbally. In these two cases the emotions towards *A* and *B* were measured and the weights used for the analysis where those of the positive attributes, just like treatments Verbal, A(+), A and Verbal, B(+), B, and therefore

[10] Colegio de Estudios Superiores de Administracion in Bogota, Colombia.

the expected relations were also positive. For treatments Verbal, A(-), A and Verbal, B(-), B, since the negative attributes were the ones manipulated, the weights towards the negative attribute were used. Therefore, the relation is expected to be negative. Table 2 summarizes the dependent variables, the independent variables and the relations expected.

Table 2. Dependent variables, independent variables and expected relation.

Treatment	Dependent	Independent	Relationship expected
1. Verbal, A(+), A	SAM to alternative A	Weight of attribute *x*	Positive
2. Verbal, B(+), B	SAM to alternative B	Weight of attribute *y*	Positive
3. Numerical A	SAM to alternative A	Weight of attribute *x*	Positive
4. Numerical B	SAM to alternative B	Weight of attribute *y*	Positive
5. Verbal, A(-), A	SAM to alternative A	Weight of attribute *y*	Negative
6. Verbal, B(-), B	SAM to alternative B	Weight of attribute *x*	Negative

Linear regressions show the following results:

Figure 2. Matrix scatter plot of weights vs. S.A.M scores per treatment.

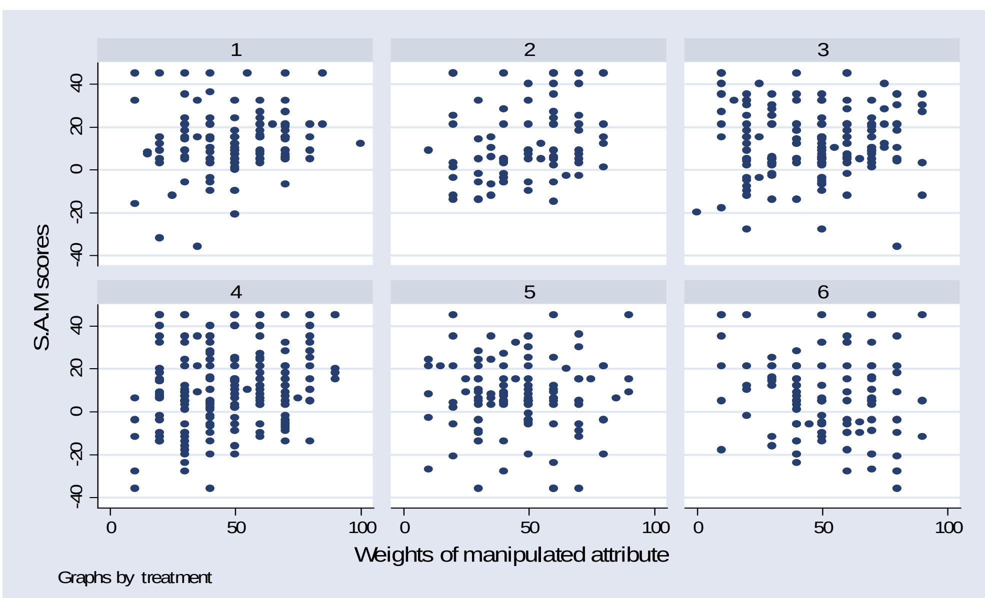


Table 3. OLS regression coefficients of weights on S.A.M scores

Treatment	Coefficient (weight)
1. Verbal, A(+), A	0.08 (ns)
2. Verbal, B(+), B	0.22*
3. Numerical A	0.01 (ns)
4. Numerical B	0.19**
5. Verbal, A(-), A	0.00 (ns)
6. Verbal, B(-), B	, 0.19*

*(ns) not sig. *p<0.05, **p<0.01*

The OLS regressions show that in treatments Verbal, B(+), B, Numerical B and Verbal, B(-), B there is a significant effect of the importance of attributes on S.A.M scores in the direction expected, particularly in treatment Numerical B. However, in the other 3 treatments no effect was found. A strong effect found in treatment Numerical B, in which all the information was presented numerically, is noteworthy. It was roughly as strong as those of the verbal treatments where there was a significant effect. This evidence is not conclusive but suggests a weak relationship between attributes and weights. Moreover, the verbal manipulation had no effect. It must be noted, in addition, that the significant relations were all between alternative *B* and attribute *y*, whereas alternative *A* and attribute *x* displayed no relation. I have no explanation for this.

H2. Effects of weights and emotions on choice

The next step is to analyze the effect of emotional reactions and weights on actual choices. The variables used were the same as in the previous analysis. A fixed effects logit model[11] was estimated for each treatment with choices as dependent variables and answers to S.A.M and the weight of the manipulated attribute as explanatory variables. Choices were coded 1 for *A* and 0 for *B*. Table 4 summarizes the variables and regressions.

Table 4. Detail of dependent and independent variables and expected effects.

Treatment	Dependent	Independents (effect expected)	
1. Verbal, A(+), A	Choice (A=1, B=0)	SAM to alternative A (+)	Weight of attribute *x* (+)
2. Verbal, B(+), B	Choice (A=1, B=0)	SAM to alternative B (-)	Weight of attribute y (-)
3. Numerical A	Choice (A=1, B=0)	SAM to alternative A (+)	Weight of attribute x (+)
4. Numerical B	Choice (A=1, B=0)	SAM to alternative B (-)	Weight of attribute y (-)
5. Verbal, A(-), A	Choice (A=1, B=0)	SAM to alternative A (+)	Weight of attribute y (-)
6. Verbal, B(-), B	Choice (A=1, B=0)	SAM to alternative B (-)	Weight of attribute x (+)

Below, I provide a more detailed account of the expected results of the regression analysis.

- Treatments Verbal, A(+), A and Numerical A: Affect (SAM towards A) and weights (of the good attribute of A) are positively associated with the probability of choosing A.

- Treatment Verbal, B(+), B and Numerical B: Affect (SAM towards B) and weights (of the good attribute of B) are negatively associated with the probability of choosing A

[11] This kind of model was necessary because the unit of analysis was each decision, where every subject made 12 of them, causing a potential problem with the independence of choices. This panel data model solves this problem by capturing the potential effect of subject style (i.e., always emotional or always reason based) in the choice process.

- Treatment Verbal, A(-), A: Affect (SAM towards A) is positively associated with probability of choosing A but weights (of the bad attribute of A) are negatively associated with the probability of choosing A

- Treatment Verbal, B(-), B: Affect (SAM towards B) is negatively associated with the probability of choosing A but weights (of the bad attribute of B) are positively associated with the probability of choosing A

Regressions show the following results:

Table 5. Coefficients of fixed effects logit regressions.

Treatment	Coeff. (S.A.M)	Coeff. (Weight)
1. Verbal, A(+), A	.071***	.050***
2. Verbal, B(+), B	- .124***	- .071***
3. Numerical A	.081***	.050***
4. Numerical B	- .070***	- .037***
5. Verbal, A(-), A	.041**	.008 (ns)
6. Verbal, B(-), B	- .054***	- .004 (ns)

Hypothesis two receives clear support. Most regressors are highly significant meaning that the probability of choosing *A* or *B* is significantly affected by both emotions and cognitions. Coefficients of the affective reactions are highly significant in all treatments. Coefficients of weights were highly significant in the direction expected in treatments Verbal, A(+), A, Verbal, B(+), B, Numerical A and Numerical B but not significant in treatments Verbal, A(-), A and Verbal, B(-), B. Remember that in these two treatments the weights used as regressors were those of the bad attributes expressed verbally (e.g., *slow* cars, *heavy* notebooks, or *slow* service).

These results show that people use both affective reactions and cognitive deliberation to choose, but when negative or inferior attributes are expressed verbally, they disregard the weight (cognitive information) of such attributes and choose largely based on affect. However, two things are worth noting: First, in spite of being mostly driven by emotion, the time employed to make choices in treatments Verbal, A(-), A and Verbal, B(-), B were not significantly slower than those of the other treatments ($t = 1.42$, $p > .1$). Second, there were significant differences in the S.A.M scores ($F = 4.95$, $p < .001$) across treatments with post hoc contrasts revealing that treatments Verbal, A(-), A and Verbal, B(-), B are the ones presenting a significantly more negative score on S.A.M than the other treatments. Finally, note that these results are based on aggregated data which were not suitable for individual analysis and whether each participant followed a particular model.

Discussion of experiment 1

Results present partial support for hypothesis one, and general support for hypothesis two. This means that both cognition and affect are relevant factors for people when making choices. Evidence suggests that both directly influence the direction and strength of preferences. In terms of the models, the results of experiment 1 support the two main assumptions underlying them. First, the discontinuous relationship of affect and cognition shows that we need models that account for both correlated and uncorrelated emotions and cognitions. However, the conditions under which each type of model applies have yet to be identified. Second, the presence/lack of correlation between weights and affect combined with the results of regressions specifically support a decision process similar to the one captured by the ACcE and ACnE model in which the value or utility of an alternative is the result of the combined evaluation of cognitive and emotional components.

Going deeper in the interpretation of the results, it could be suggested that finding a significant relation of weight and affect only in some treatments means that, for the participants in these experiments, the fact that an attribute is regarded as important did not imply that an affective reaction is necessarily triggered when such an important attribute is salient to the target.

The role of verbal and numerical information as proxy for more or less emotionally accessible content received limited support. Differences in the S.A.M. scores were only found for the negative verbal treatments (Verbal, A(-), A and Verbal, B(-), B) but not for the positive ones (Verbal, A(+), A and Verbal, B(+), B). In addition, even though the results of logit regressions show that, in the presence of negative verbal information, only the emotional assessment about the alternative was a significant predictor of choices, it must be noted that the effect of emotion on the probability of choice is positive. This fact indicates that the emotion that influenced the preference was not the negative one exclusively (triggered by the "bad" verbal attribute), but the net emotional effect of the negative and the positive (triggered by the "good" numerical attribute). This way, the negative verbal information did not seem to produce an immediate rejection of the alternative that contains it . Instead, it seemed to affect the way in which people used their whole range of affective reactions. In other words, the verbal negative information caused people to focus more and give more relevance to their feelings as valid information for the construction of preferences.

In summary, this experiment has shown that the proposed models of choice have the potential to capture the process of construction of preferences including information of a cognitive-affective nature. In particular, the results of testing H1 and H2 suggest that models ACcE and ACncE, where cognition and emotions are mixed, are the most likely representations of choice processes. Reason and affect show some degree of relation, but somehow, participants seem to be able to decide on how this information is evaluated (e.g., in treatment Verbal, B(-), B, there is a significant relation between the affect towards B and the weight of attribute *x*, but the weight did not show a significant effect on choice). Therefore, it is necessary to understand better the source of such procedural considerations. It is also necessary to understand deeper the nature of cognitive and emotional evaluations of alternatives to clarify the conditions under which they are and are not interdependent. There are also open questions on the reasons why positive and negative situational expressions of the same information trigger a different effect in the decision process. In particular, why does negative content drive people to rely more on affect and how does this occur? This experiment showed that the assumptions made on the formulation of the models are reasonable and the major result is that models that use cognitive-affective information seem to represent the actual decision process better.

EXPERIMENT 2

The aim of this experiment is to investigate further the findings of experiment 1, and test the predictive power of the models. In order to do so, it is necessary to extend the theoretical context of the research. In the following section I outline the theory that can help to explain the results of experiment 1 and state the purposes and hypotheses of experiment 2.

Self regulation of emotion and affect in choice

When people make choices, they have to balance the cognitive-affective component provided by attributes of options. For instance, a person choosing a way of transportation to go to work, may have good feelings about taking a bus, enjoying the sun in a beautiful morning. She knows, however, that time is important, and therefore by taking the dark subway she will arrive sooner with less risk of a delay. Thus, she trades off one combination of feelings and speed for another combination of feelings and speed, because there is also a positive feeling of avoiding the risk of arriving late at work. These kind of competitive cognitive-affective judgments are the basis of the models proposed in the present research.

The notion of a complementary system of decision making in which reason and affect determine *together* the preferred alternative received support in experiment 1. It was found that both affective reactions and cognitive weights (i.e., reason) are determinant in shaping people's preferences. However, it seems that the way cognitive-affective information is used and traded off involves some kind of monitoring.   In particular, experiment 1 suggested that the valence of emotions triggers such procedural considerations leading people to rely heavily on emotional cues when negative feelings are salient during the decision process. Positive feelings did not display this effect, and on the contrary, they seem to work together with cognitive activity. This result is remarkably consistent with the work of Tice, Baumeister and Zhang (2004). They review several pieces of research showing how positive and negative emotions play a distinct and different role in self-regulatory processes. In particular, they find that negative affect undermines self regulatory behaviors in different domains, while positive affect, on the other hand, not only works together with self regulation, but also helps to replenish the self regulatory capacity of individuals. The similarity with the present work is that, according to Tice et al., negative emotion takes priority (such that people regulate these feelings) in people's behavior, leading them to regulate these negative feelings before other functions of self regulation are exercised. This may explain why people in experiment 1, in treatments with negative verbal information, gave more relevance to their feelings in the determination of preferences.

Tice et al. also show that self regulatory capacity operates like a rechargeable battery that can be depleted by simple tasks, changing behavioral patterns. This way, if it is true that the role of affect in decision making is somehow monitored by the individual, then, the depletion level of cognitive resources should play a role in the way cognitive-affective information is used during the construction of preferences.

Thus, the second experiment aims to extend the results of experiment 1 by studying whether the role of cognitive and affective forces in choice are related to a self regulatory activity during decision making. The goal is to provide a deeper account of the nature of the interplay of reason and affect and an explanation of the results obtained. With this purpose, I introduce an experimental device aimed at depleting the self regulatory capacities of individuals. In the following paragraphs I provide a deeper explanation of the relation of the work of Tice et al. with the present research and how I introduce their findings in the second experiment.

It must first be remarked that the work of Tice, Baumeister and Zhang (2004), does not deal directly with choice. However, as stated, the principles of self regulation that they establish are highly compatible with the phenomena of reason and affect studied in the present work. They find that people experiencing negative emotions tend to engage in behaviors that help to reduce the unpleasant feelings, even if such behaviors are not consistent with other desirable goals. For example, keeping a diet is something that requires an effort of self regulation.

People must refuse to eat appealing tasty food in order to achieve the benefits expected from the diet. Tice et al. argue that under negative emotions, the short term benefit of suppressing the bad feeling takes priority in people's goals. This way, people experiencing bad feelings are more inclined to break a diet, as long as they believe that eating the unhealthy food will make the negative emotions go away. In their words "Affect regulation takes priority over other programs of self regulation. It does not require any suggestion that emotional distress actually reduces one's capacity for self regulation. Rather, all it means is that when affect regulation is in conflict with some other form of self regulation, one or the other has to be given priority" (Tice et al, 2004; p. 214). The necessary condition for this priority shift to happen, is that people believe they have the capacity to influence their affective states. The authors do not specify whether this belief is conscious or not.

In the realm of choice, I found in the previous experiment that when negative feelings are more salient during the decision process, people tend to base their preferences heavily on the affective component of information. This way, negative emotions drive people to pay less attention to cognitive information and to focus their efforts instead on balancing out the positive and negative feelings triggered during the decision process.

The similarities of the present work and that of Tice et al. lead to the formulation of the following hypotheses:

H3: The presence of negative feelings leads people to increase their reliance on affect as a component of their preferences.

If the affective focus in the presence of negative verbal attributes in choice is driven by the same principle explained by Tice et al., then the determination of preferences includes a self regulatory activity that minimizes negative feelings. This forces participants to engage in complex deliberations about their emotions, leading them to develop preferences for the way cognitions and emotions are combined during the decision process and for the extent to which emotions influence the final choice, that is, what I call procedural preferences.

H4: The depletion of the self regulatory capacity increases the use of emotional information in the construction of preferences.

Dealing with negative feelings during the decision process is difficult and takes effort. If participants are depleted, then the self regulation of such negative emotions is given priority by participants, increasing the relevance of emotional information in the construction of preferences.

In addition to testing H3 and H4, results from experiment 2 will be also used to:

1. Provide additional evidence to analyze H1 and H2, by including full measurement of emotions (i.e., for both alternatives)
2. Fit at the individual level the decision making models proposed earlier, in order to assess their accuracy and appropriateness as representations of the cognitive-affective processing of information during the construction of preferences.
3. Study whether the theory of self regulation of emotion is appropriate to explain the results of this research, extending and adjusting such theory to fit the realm of

choice, and providing a psychological basis for the characterization of the interplay between reason and affect that has been proposed.

Method

The task: The task is basically the same as used in experiment 1. Each participant made 12 binary decisions (choose between *A* and *B*) where each alternative is described by two attributes (*x* and *y*) and each alternative is better than the other on one attribute. There are two major modifications: First, emotions are measured for both alternatives, *A* and *B* on each choice. Second, there is no pretest of verbal-numerical equivalencies to produce customized tasks. Instead, the average numerical equivalents provided by participants in experiment 1 are used in the tasks of experiment 2. This yields a design with 5 treatments.

Table 6. Summary of treatments and treatment names for experiment 2.

		Verbally expressed attributes				
		Good attribute of A [A(+)]	Good attribute of B [B(+)]	Bad attribute of A [A(-)]	Bad attribute of B [B(-)]	All numerical
Measurement of emotions	Towards A and B	*Verbal,A(+)*	*Verbal,B(+)*	*Verbal, A(-)*	*Verbal, B(-)*	*Numerical*

Emotions towards *A* and *B* were measured using again the S.A.M. instrument for all choice problems. This measurement was performed separately from the choices. It was also randomized separately from the choices. Therefore, the random order of the choices did not match the random order of the emotional measures. This way participants answered the questions about their emotions and the choice problems separately, controlling the possibility of having participants trying to be consistent between their choices and the emotions they report (e.g., if I choose A, then my emotions towards A should be more positive than my emotions towards B)

Depleting task: Half of the participants completed the choice task after an ego depleting task. The purpose of this was to exhaust their self regulatory capacities right before entering the choice task. I asked the participants to solve an extremely difficult sudoku[12] game, in which the usual numbers were replaced by letters. They were instructed to place as many letters as possible in ten minutes and their final payment was partially determined by the number of correctly placed letters.

The idea behind this manipulation is the following: If (a) the holistic emotional reaction is a combination of biological, conditioned and deliberative components and (b) the way people use their emotions involves some kind of monitoring (i.e., procedural preferences), then people may change the way in which emotions are used in the construction of preferences as a result of the depletion of self regulatory capacity.

Participants: The tasks were completed by 106 undergraduate students recruited on campus at Pompeu Fabra University. 56 were randomly assigned to the non-depleted condition and 60 to the depleted condition. They received a flat fee of 5 euro for their participation and those in the depleted condition received additional money according to the number of correct answers in the sudoku game, at a rate of 0.20 cents for each correctly placed letter. The average remuneration was 7 euros The experiment was programmed in the "LeeX" laboratory at Pompeu Fabra (LeeX) using the zTree software, which automatically recorded participants' answers.

[12] See appendix 2 for an explanation of the verbal sudoku.

Results

H1. Relation between weights and emotions

Similarly to experiment 1, I analyze the effect of weights on emotional responses. Experiment 1 revealed that this relationship might be significant, therefore the goal in experiment 2 is to test the relationship, this time using the data collected on the emotional reactions towards the two alternatives (i.e., *A* and *B*). In addition, the analysis is performed separately for depleted and non depleted participants in order to look for differences caused by these two conditions. Linear regressions with the S.A.M. answers as dependent variables and weights as independent were performed for each treatment. For S.A.M. responses towards alternative *A*, weights to attribute *x* were used as predictors and symmetrically, for S.A.M. answers to *B*, weights to attribute *y* were used as predictors. This way, the expectation is that in all cases weights have a positive effect on the emotional reaction measured by S.A.M. Weights to both *x* and *y* cannot be included simultaneously because they are perfectly negatively correlated. Table 7 summarizes the regressions performed and the results expected. The same analysis is performed twice, once for the depleted participants and once for the non depleted.

Table 7. Summary of OLS regressions of weights on S.A.M. answers, experiment 2.

Treatment	Dependent	Independent	Relationship expected
1. Verbal, A(+)	SAM to alternative A	Weight of attribute *x*	Positive
2. Verbal, B(+)	SAM to alternative A	Weight of attribute *x*	Positive
3. Numerical	SAM to alternative A	Weight of attribute *x*	Positive
4. Verbal, A(-)	SAM to alternative A	Weight of attribute *x*	Positive
5. Verbal, B(-)	SAM to alternative A	Weight of attribute *x*	Positive

Treatment	Dependent	Independent	Relationship expected
1. Verbal, A(+)	SAM to alternative B	Weight of attribute *y*	Positive
2. Verbal, B(+)	SAM to alternative B	Weight of attribute *y*	Positive
3. Numerical	SAM to alternative B	Weight of attribute *y*	Positive
4. Verbal, A(-)	SAM to alternative B	Weight of attribute *y*	Positive
5. Verbal, B(-)	SAM to alternative B	Weight of attribute *y*	Positive

Figures 3.1 to 3.4 and table 8 summarize the regression results.

Figure 3.1. Scatter plot of the effect of weight of *x* on emotions to *A* per treatment. Non depleted participants.

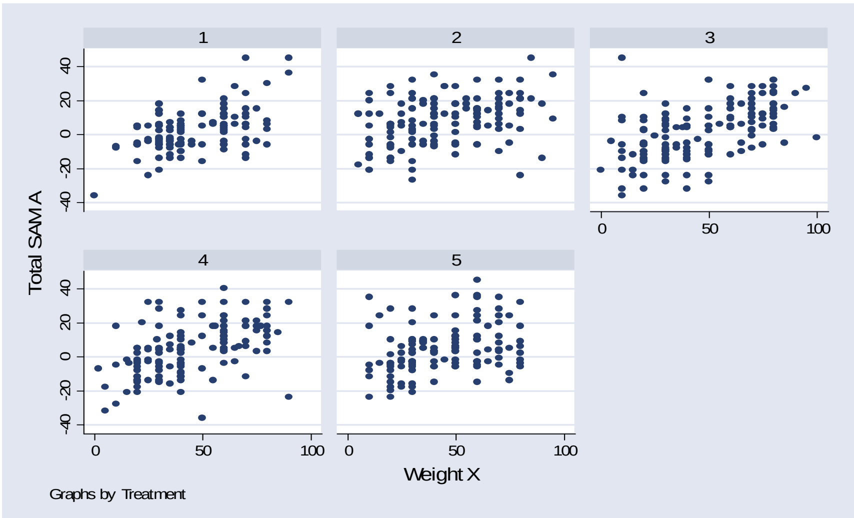


Figure 3.2. Scatter plot of the effect of weight of *y* on emotions to *B* per treatment. Non depleted participants.

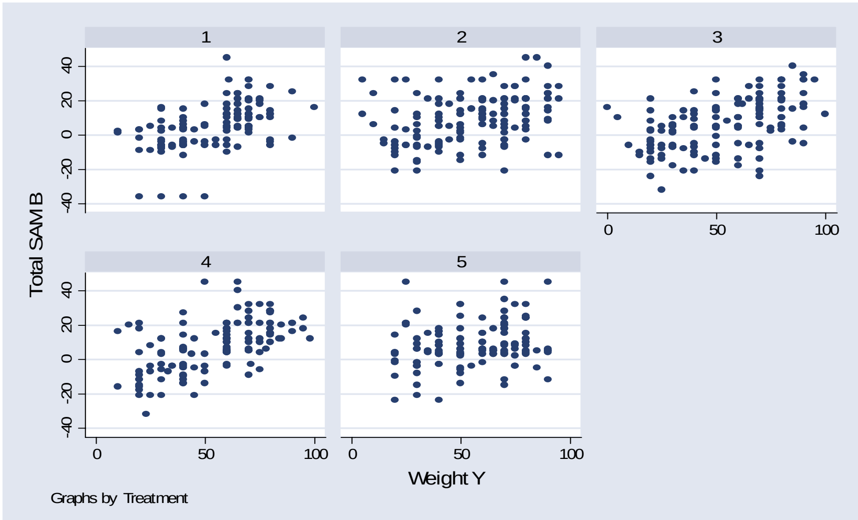


Figure 3.3. Scatter plot of the effect of weight of *x* on emotions to *A* per treatment. Depleted participants

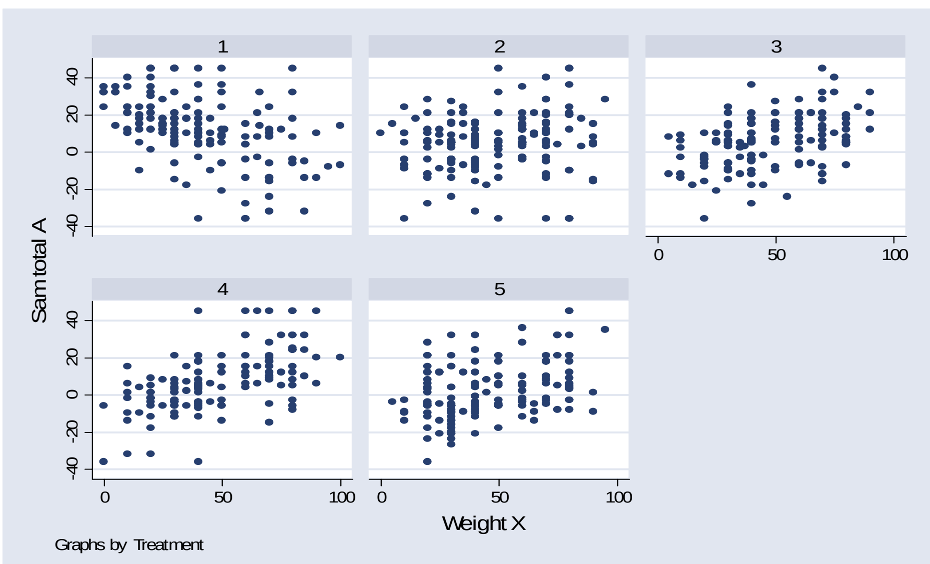


Figure 3.4. Scatter plot of the effect of weight of *y* on emotions to *B* per treatment. Depleted participants.

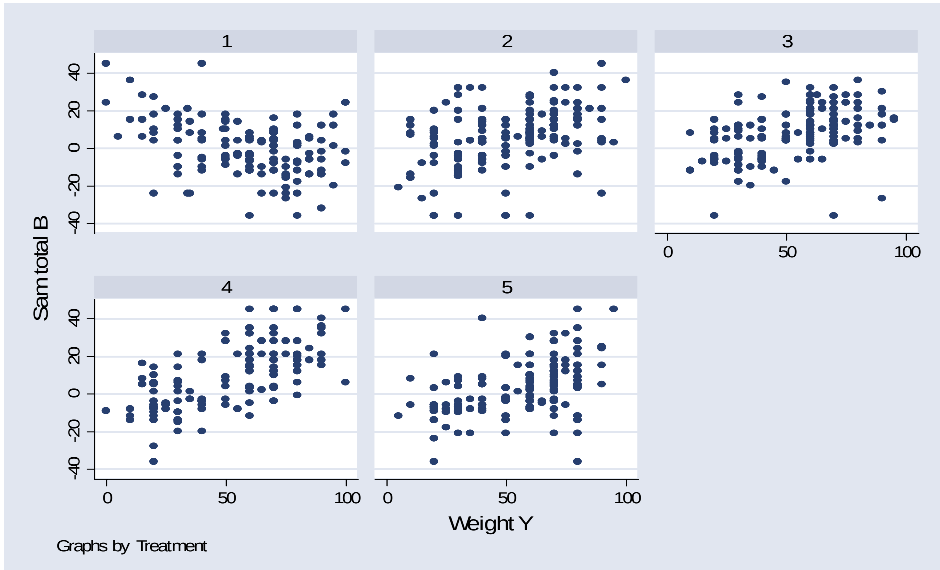


Table 8. Standardized regression coefficients of weights on S.A.M. answers.

Treatment	Non depleted		Depleted	
	Weight X (to SAM A)	Weight Y (to SAM B)	Weight X (to SAM A)	Weight Y (to SAM B)
Verbal, A(+)	0.48**	0.49**	- 0.46**	- 0.37**
Verbal, B(+)	0.37**	0.34**	0.14 ns	0.41**
Numerical	0.53**	0.52**	0.40**	0.44**
Verbal, (B-)	0.50**	0.58**	0.58**	0.65**
Verbal, B(-)	0.32**	0.22**	0.36**	0.45**

(ns) not significant (*) p < 0.05, (**) p < 0.01

Experiment 2 reveals a strong relation between weights and emotions, giving a stronger support for H1 than the data from experiment 1. All except one relationship are highly significant, showing that there is a clear effect of weight on emotions. However, it is also clear by looking at the data and figures that weights are not the only force driving emotional reactions. Supporting this claim, look at the differences between the coefficients of depleted and non depleted condition in table 8. Note that the signs of the coefficients in treatment Verbal, A(+) of the depleted participants are negative instead of positive as expected. In this treatment, the superior/positive attribute of alternative *A* was expressed verbally. In addition, in treatment Verbal, B(+), one of the coefficients is insignificant in the non depleted condition. Further in the paper I explore the reasons behind such behavior. So far there is evidence supporting that cognition and affect play a complementary role in the mind of decision makers. Therefore, decision making models should account for cognitive-affective pieces of information in the expression of preference.

H2. Effects of weights and emotions in choice

Similarly to experiment 1, I analyze the significance of weights and emotions on the probability of choosing *A* or *B*. As opposed to experiment 1, this time there are data on affective reactions to both alternatives, *A* and *B*. This way, choices of *A* were coded 1 and choices of *B* were coded 0. That is the dependent variable. As independent variable I use the S.A.M. answers towards *A*, the S.A.M. answers towards *B* and weights of attributes *x*. Again, weights of attributes *y* cannot be used because of perfect negative correlation with weights of attribute *x*. Under this framework, the expected results are: (1) that S.A.M. answers to *A* have a positive effect on the probability of choosing *A*, (2) S.A.M. answers to B have a negative effect on the probability of choosing *A,* and (3) weights of attribute *x*, (given that attribute *x* is the superior attribute in alternative *A)*, have a positive effect in the probability of choosing *A*. In addition, the analysis is done separately for depleted and non depleted participants. I estimate a fixed effects logit regression first with the data of all decisions (760 in the depleted condition and 672 in the non depleted condition) and then I estimate the model by treatment. Table 9 summarizes the variables and expected effects of the regression analysis.

Table 9. Summary of variables and effects of fixed-effect logit regressions.

Treatment	Dependent	Independents (effect expected)		
Verbal, A(+)	Choice (A=1, B=0)	SAM to alternative A (+)	SAM to alternative B (-)	Weight of attribute *x* (+)
Verbal, B(+)	Choice (A=1, B=0)	SAM to alternative A (+)	SAM to alternative B (-)	Weight of attribute *x* (+)
Numerical	Choice (A=1, B=0)	SAM to alternative A (+)	SAM to alternative B (-)	Weight of attribute *x* (+)
Verbal, A(-)	Choice (A=1, B=0)	SAM to alternative A (+)	SAM to alternative B (-)	Weight of attribute *x* (+)
Verbal, B(-)	Choice (A=1, B=0)	SAM to alternative A (+)	SAM to alternative B (-)	Weight of attribute *x* (+)

Table 10 summarizes the results. Note that regressions were performed for the whole sample, only divided in depleted and non depleted, and then segmented by treatment.

Table 10. Coefficients of Fixed effects logit regression of S.A.M. scores and weights on Choices.

Non depleted subjects (by treatment)			
Treatment	SAM to A	SAM to B	Weights
Verbal, A(+)	ns	ns	0.14**
Verbal, B(+)	ns	ns	0.13**
Numerical	0.09**	- 0.08*	0.09**
Verbal, A(-)	ns	ns	0.09**
Verbal, B(-)	0.13**	ns	0.16**
Depleted subjects (by treatment)			
Treatment	SAM to A	SAM to B	Weights
Verbal, A(+)	ns	ns	0.09**
Verbal, B(+)	ns	ns	0.12**
Numerical	0.06*	- 0.08**	0.08**
Verbal, A(-)	ns	- 0.14*	0.12*
Verbal, B(-)	0 09*	- 0.06*	0.12**
Depleted Subjects (Aggregated)			
	SAM to A	SAM to B	Weights
	0.02*	- 0.03**	0.11**
Non depleted Subjects (Aggregated)			
	SAM to A	SAM to B	Weights
	0.05**	ns	0.11**

(ns) not significant (*) p < 0.05, (**) p < 0.01

Regression results provide weaker support for H2 than those in experiment 1. The effect of weights on the probability of choice is observable across all treatments but the effect of emotions is not as general as it appeared in experiment 1. Note that for the analysis of experiment 2, I included the measurement of emotions towards both attributes whereas in experiment 1 I included as regressors the emotions towards one alternative only. The instances at which emotions are significant or not, are the object of the analysis of H3 and H4.

I analyze H3 (*The presence of negative feelings leads people to increase their reliance on affect as a component of their preferences*) and H4 (*The depletion of the self regulatory capacity increases the use of emotional information as part of the construction of preferences*) together because results reveal an interaction of negative feelings and depletion level.

First of all, depleted participants use their emotions more than non depleted participants supporting H4. This can be seen at the aggregated level where the depleted participants made significant use of weights, emotions to *A* and emotions to *B*, while the non depleted participants disregarded the emotions towards *B*. The analysis per treatment reveals further details of this finding. Note that emotions have a significant effect more often in decisions made under the depleted condition.

Once again, the assumption that verbal information infuses more emotional content to attribute information is difficult to sustain. It seems to depend on affective valence and depletion. In treatments Verbal, A(+) and Verbal, B(+), where the positive attributes were expressed verbally, only weights show a significant effect on the probability of choice. In treatments Verbal, A(-) and Verbal, B(-), where the negative attributes were the ones expressed verbally, emotions have a strong impact on the probability of choice thereby supporting H3. However, this occurs mostly in the non depletion condition, suggesting that depleted participants were more prone to use their emotions when negative information was presented verbally.

Interestingly, in the Numerical treatment, for depleted and non depleted participants, where all the information was presented numerically, both weights and emotions have a significant effect on the probability of choice across all treatments. There was no hypothesis regarding this finding. This might be interpreted as if numbers have more emotional impact than verbal information. However this finding could be an additional indicator of the presence of procedural preferences regarding the use of cognitions and emotions, where consistent information (i.e., all numerical) makes people use both types of cues. I elaborate on this idea later on.

Overall, there is strong support for H1, finding evidence of the relation between weights and emotions. There is mixed evidence on H2, suggesting that the combined effect of emotions and weights in choice is mediated by situational variables. Regarding H3 and H4, findings indicate that valence of feelings and depletion level of participants exert an effect on the way cognition and affect are used in the construction of preferences.

The main result of experiment 2 is that the effect of emotions in choice cannot be understood looking at the “direct” or “automatic” impact of an emotional reaction in behavior. This means that the effect of emotions does not seem to be like: “I feel something good (bad), then I prefer (reject) it”. Rather, we should look at two aspects First, the effect of emotions on preferences seems to depend on how people perceive and analyze the consistency and appropriateness of cognitive and affective information during the decision process. This perception leads to judgments about the extent to which cognitive and emotional drivers are allowed to influence the final choice (i.e., what I call procedural preferences) . Second, emotions felt while making decisions do not seem to be a holistic and unique reaction. Instead, people seem to be able to separate and differentially use diverse emotions that are felt throughout different stages of the decision process.

Discussion of experiment 2.

As suggested, one possible interpretation of the results of experiment 1, is that people have some degree of control over the balance of cognition and emotion in the construction of preferences. Experiment 2 shed additional light on that idea. Regressions of weights on emotions revealed a pervasive relation of cognition and affect, therefore, the emotional component is present in all treatments. However, the way cognition and affect influenced preferences varied as a function of two things: First, the depletion of self regulatory capacity of individuals, and second, the verbal vs. numerical presentation of attributes. These results can be explained if we analyze the procedural effect of the verbal numerical manipulation instead of its direct emotional effect.

When making decisions in these experiments, participants faced a mixture of verbal-numerical information, or purely numerical information. As expected, the mixed information complicates the way in which trade-offs are performed. Compensating a verbal attribute with a numerical one probably implies more cognitive effort than compensating two numerical attributes. Such experiences possibly triggered emotions of a meta cognitive nature and activated procedural preferences favoring consistent information.

As mentioned in the review of the literature, performing trade offs has been found to impose a negative emotional cost on participants (e.g., Luce, Payne and Bettman, 2001). If we add this meta cognitive complication to the depletion task, it follows that depleted participants found it more difficult to perform the verbal numerical trade offs. This fact would explain the puzzling inverse relationship of weights and emotions found in treatment one in the depletion condition (see table 8). The more important the attribute is, the harder the trade off, triggering negative emotions towards the alternative that contains the verbal attribute. Non depleted participants on the contrary had more resources to perform the trade offs and therefore did not experience such negative emotion.

Looking at the logit regression results, the trade off analysis also explains how emotions were used differently across treatments. First of all, people in the purely numerical treatments experienced the simplest procedural problem, trading off only numbers. They probably felt more comfortable letting their direct emotions towards the target alternatives influence their choices because of the consistency of information, which is procedurally convenient. Contrastingly, those experiencing the difficulty of verbal/numerical trade offs, regardless of being depleted or non depleted, tended to balance their procedural preferences in favor of the cognitive component, particularly when positive information was expressed verbally. However, when the negative information was the one expressed verbally, being depleted had an effect. Participants under this condition allowed a greater influence of emotions on their preferences.

As explained in the experimental design, the role of ego depletion gains relevance particularly when people deal with negative emotions. This way, self regulation of emotions was not triggered in the presence of positive verbal information, but it was in the presence of negative verbal information. It follows that depleted people in the negative treatments were able to perform the trade offs over positive numerical information but found it difficult to disregard the negative feelings triggered by the negative verbal information. This way, negative verbal attributes became the focus of self regulation attention, which was exercised by letting it influence their preferences. Meanwhile, depleted participants in the positive treatments could perform the trade offs over the numerical negative information and focused on the procedural problems of the positive information, favoring the cognitive side of information, just like the non depleted participants.

FITTING THE MODELS

Experiment 2 provides sufficient data to fit the four proposed models at the individual level and assess their accuracy as representations of the choice process with cognitive-affective information. So far, results of experiments one and two seem to support models two and three, in which information is processed in a cognitive-affective way, whereas models one and four, for which information processing is purely cognitive or purely emotional respectively, seem to be less accurate accounts of the actual decision procedure. However, the experimental results also suggest that across the different treatments the appropriate model may vary. Therefore, the purpose of the following section is to explore how well each model fits participants' actual choices in each treatment, paying particular attention to the differences between depleted and non depleted participants. In addition fitting the models should also shed additional light on the interpretation of the results from experiment 1 and two. In this section, I briefly recall the definition of each model presented at the beginning of the chapter and then explain, for each case, some necessary adjustments and additional assumptions necessary to fit the data. I use the data only from experiment 2.

Model 1 (ACC)

This model was based on previous literature and it is assumed to be a representation of purely cognitive processing. It was defined in previous sections (equation 1) as:

$$A_j = \sum_{i=1}^{n} w_{ij} x_{ij}$$

Where x corresponds to the value of attribute i and w is the cognitive weight given to attribute i. It has an additive compensatory structure and therefore I will henceforth refer to it as the ACC model (Additive, Compensatory, and Cognitive). To fit the data, there is a problem of scale comparability among the different attribute scales (the x's). Therefore, I do not use the direct value of the attribute. Instead I define the utility of the attribute value $u(x_i)$ in the following way.

$$u(x_i) = \begin{cases} 1 & \text{if } x_i \text{ is the superior attribute} \\ 0.5 & \text{if } x_i \text{ is the inferior attribute} \end{cases} \qquad (5)$$

Thus, there is a common representation of the value of attributes for decision makers under the assumption that given two different values of the same attribute, participants prefer one (the good) over the other (the bad). The two values are clearly distinguishable from each other since they are the result of the pre test performed in experiment 1, where participants gave their numerical equivalents of opposite categories (e.g. fast and slow). Recall that the actual values presented to participants in experiment 2 are the averages of the numerical equivalents given by participants of experiment 1.

In addition, the values of the weights (*w´*s) were transformed into quantities on the [0,1] interval using the 0 -100 original estimates given by participants. I just divided the answers by 100 to get the 0 – 1 figure. This way, the actual model to fit to data is the following:

$$A_j = \sum_{i=1}^{n} w_{ij} u(x)_{ij} \qquad \text{where} \qquad \sum_{i=1}^{n} w_{ij} = 1 \qquad \text{and} \qquad u(x_{ij}) \in \{0.5, 1\} \tag{6}$$

Model 2 (ACcE)

This model includes emotions as part of the total weight given to an attribute. Weights are therefore assumed to be a combination of cognitive and affective judgments where the affective judgment is significantly influenced by the cognitive weight. It was defined previously (equation 2) as:

$$A_j = \sum_{i=1}^{n} \left[w_{ij}^{c} + w_{ij}^{e}(w_{ij}^{c}) \right] x_{ij}$$

In this model, recall that w_{ij}^{c} is the cognitive part of the total weight, and $w_{ij}^{e}(w_{ij}^{c})$ is the affective part of the total weight, which is a function of the cognitive one. In order to fit the individual data, several steps must be taken. First, the assumption concerning $u(x_i)$ is again utilized. Second, the answers given by participants regarding weights of attributes are used as a measure of w_{ij}^{c} and again recalculated in the [0,1] interval. Finally, the affective part of the weight is calculated. To do this, I assume that the affective weight is a linear function of the cognitive weight (i.e., $w_{ijk}^{e}(w_{ijk}^{c}) = \alpha_{ijk} + \beta_{ijk} w_{ijk}^{c} + \varepsilon_{ijk}$). Looking at the scatter plots (figs. 5,1, to 5.4) there is no suggestion of a non-linear relation. Note this function is estimated for each treatment *k*, given that, as established previously, I treat weighing judgments as local, which means that they depend on the characteristics of the particular decision under evaluation. I assume additionally that $\varepsilon_{ijk} = 0$[13] and α_{ijk}, that correspond to emotions not related to cognitive weights, are also assumed to be 0. This way, taking all these elements into account, the model actually fitted to the data is the following.

$$A_{jk} = \sum_{i=1}^{n} \left[w_{ijk}^{c} + \beta_{ijk} w_{ijk}^{c} \right] u(x_{ijk}) \quad \text{where} \quad \sum_{i=1}^{n} w_{ijk}^{c} = 1 \quad \text{and} \quad u(x_{ij}) \in \{0.5,1\} \quad (7)$$

Betas are estimated by linear regressions with S.A.M. answers (to *A* and *B*) as dependent variables and cognitive weights (to attributes *x* and *y* respectively) as independent variables. S.A.M. answers are rescaled from their [-36 to 45] scale into a [-1 to 1] scale. Weights are used in its [0,1] version. This way all variables are redefined in the same scale. Table 5 displays the betas estimated from regressions. These were later used to calculate the predicted choice using the model, which is called ACcE (Addidive, Compensatory with correlated Emotions).

[13] This is a standard assumption of linear regressions

Table 11. Non standardized regression coefficients used in calculating the model 2[14].

Treatment	Non depleted		Depleted	
	Weight X (to SAM A)	Weight Y (to SAM B)	Weight X (to SAM A)	Weight Y (to SAM B)
Verbal,A(+)	0.75**	0.82**	-0.85**	- 0.55**
Verbal, B(+)	0.54**	0.49**	0.21 ns	0.73**
Numerical	0.87**	0.77**	0.61**	0.67**
Verbal, A(-)	0.85**	0.96**	0.94**	1.11**
Verbal, B(-)	0.54**	0.34**	0.62**	0.73**

(ns) not significant (*) p < 0.05, (**) p < 0.01

Model 3 (ACncE)

This model assumes that cognition and emotion are mainly uncorrelated, allowing participants to include other sources of affect in their preferences. It was defined (equation 3) as:

$$A_j = \sum_{i=1}^{n} w_{ij}^c x_{ij} + e_j(x_{ij})$$

The cognitive weight w_{ij}^c is the one reported by participants and $e_j(x_{ij})$ is the emotional reaction towards alternative *j* and it is a function of the attribute values. To fit the data, I make again the assumptions on $u(x_i)$ and transform weights into the [0,1] interval. Emotions are taken directly from the S.A.M. answers and also transformed into quantities within a [-1,1] interval. It is important to add the treatment *k* contextualization given the

[14] These results are different from table 3 because in that one, the original data on S.A.M. scores (from – 36 to 45) and weights (from 0 to 100) were used. In table 11, the regressions are performed using the transformed and comparable data (S.A.M scores from -1 to 1, and weights from 0 to 1) This way, it is possible to give a direct and correct interpretation of the regression coefficients.

following model, which was the one actually fitted to the data. The model is named ACncE (Additive, Compensatory, with non correlated Emotions).

$$A_{jk} = \sum_{i=1}^{n} w_{ijk}^{c} u(x_{ij}) + e_{jk}(x_{ij}) \text{ where } \sum_{i=1}^{n} w_{ijk}^{c} = 1,\ u(x_{ij}) \in \{0.5,1\} \text{ and } e_{jk}(x_{ij}) \in [-1,1] \quad (8)$$

Model 4 (E)

This is an emotion based model, where preferences are directly inferred by participants from the net emotion derived from their affective reactions to attributes. It was defined (equation 4) as:

$$A_{j} = \sum_{i=1}^{n} e_{ij}(x_{ij})$$

To fit the data, I have the holistic reaction towards the alternatives captured by S.A.M. answers. I again transformed the S.A.M. scores into quantities within a [-1,1] interval and fit the following model, adding the treatment differentiation *k*. The model is named E (Emotional)

$$A_{jk} = e_{jk}(x_{ij}) \quad (9)$$

Results

I estimated the four models, finding a high level of fit. Table 12 contains the results. They are divided by treatment, separating depleted and non depleted participants. Note that the unit of analysis is each single decision, and the figures reported are the percentage of correctly predicted decisions in each treatment. It could also be possible to report the average number of correctly predicted choices by subject in each treatment, but that would lead to exactly the same figures.

Table 12. Percentage of correctly predicted decisions by model.

Summary of Model Fit Depleted Subjects				
	Model			
Treatment	ACC	ACcE	ACncE	E
Verbal, A(+)	0.90	0.80	0.32	0.19
Verbal, B(+)	0.90	0.90	0.76	0.65
Numerical	0.87	0.87	0.92	0.88
Verbal, A(-)	0.93	0.93	0.96	0.95
Verbal, B(-)	0.89	0.88	0.79	0.76
Average	0.89	0.88	0.75	0.68
Non depleted subjects				
Verbal, A(+)	0.93	0.93	0.90	0.84
Verbal, B(+)	0.90	0.88	0.78	0.76
Numerical	0.92	0.88	0.88	0.85
Verbal, A(-)	0.88	0.88	0.84	0.80
Verbal, B(-)	0.87	0.90	0.80	0.73
Average	0.90	0.89	0.84	0.80

Additionally, I calculated the intermodel agreement, trying to capture to what extent models predict the same patterns of choices, or on the contrary, different models make different predictions. The results of this analysis may help to identify to what extent the models complement or overlap each other. If there are complementarities, this means that the predictive mistakes of one model may be compensated by those of the other models. If there is redundancy, the models make the same mistakes.

Table 13. Percentage of intermodel agreement.

		Depleted			Non Depleted		
Treatment	Model	ACC	ACcE	ACncE	ACC	ACcE	ACncE
Verbal, A(+)	ACcE	0.82			100		
	ACncE	0.31	0.31		0.93	0.93	
	E	0.17	0.22	0.86	0.83	0.83	0.91
Varbal, B(+)	ACcE	100			0.90		
	ACncE	0.76	0.76		0.76	0.77	
	E	0.63	0.63	0.88	0.72	0.73	0.96
Numerical	ACcE	100			0.90		
	ACncE	0.86	0.86		0.88	0.83	
	E	0.80	0.80	0.94	0.84	0.79	0.96
Verbal, A(-)	ACcE	100			100		
	ACncE	0.95	0.95		0.86	0.89	
	E	0.92	0.92	0.97	0.85	0.85	0.96
Verbal, B(-)	ACcE	99			0.86		
	ACncE	0.79	0.78		0.80	0.77	
	E	0.74	0.73	0.94	0.71	0.68	0.92

The first finding to note is the high level of predictability achieved by the four models. In particular, the purely cognitive (ACC) and the one with correlated cognitions and emotions. (ACcE). However, there are several facts that need to be addressed. First, the depletion level of participants seemed to play a salient role in the way people used cognitive-affective information in the construction of preferences. While the non depleted participants displayed a very similar pattern of choice across all treatments, depleted participants seemed to use different approaches. In particular, note how the ACncE and E models performed very poorly in treatment Verbal, A(+) and were almost one hundred percent accurate in treatment Verbal, A(-). Treatment Verbal, A(+) and Verbal, A(-) were the ones where, respectively, the good and the bad attribute of alternative *A* was expressed verbally. Treatment Verbal, A(+) was also the treatment under which the correlation of weights and

S.A.M. answers was negative. This way, for depleted participants in this treatment, there was a clear emotional response towards the alternatives, but this reaction seemed more related to the difficulty of performing trade offs with verbal information as I have already suggested. The result of the model fitting analysis provides additional information revealing that such emotional reaction was not included as information in the construction of preferences, supporting the notion that participants develop procedural preferences in relation to how emotional cues are used. On the contrary, in treatment Verbal, A(-) they seemed to give a lot more relevance to the affective state, probably driven by the need of negative emotion regulation.

Overall, the models that fit the data better are ACC and ACcE. The similar performance of these two models is attributable to the high correlation of weights and S.A.M. answers. Note, however, that their intermodel agreement was almost perfect for depleted participants whereas it decreased for non depleted participants. The ACncE model also presented a good fit, but its performance was significantly affected both positively and negatively by the depletion level of participants. Interestingly, this model outperformed the rest in the purely numerical treatment for depleted participants, while its performance fell in other treatments. In addition, the intermodel agreement with ACC and ACcE is not too high considering the high level of predictive power of the three models, which means that ACncE succeeded where ACC and ACcE failed, complementing each other. The behavior of model ACncE gives additional support to the idea that people are more keen on allowing their emotions to actually influence their preferences when information is consistent and tractable (i.e., purely numerical). Model E presents a high level of variability in its predictive power, particularly for depleted participants. The poor performance of E in treatment Verbal, A(+) compared to its very good performance in treatment Verbal, A(-)

may be attributable to the way people interpreted their feelings. In treatment Verbal, A(+), where the correlation of weights and S.A.M. scores was negative, emotions are probably related to meta cognitive experiences, making people keen on disregarding such emotions as part of their preferences, whereas in treatment Verbal, A(-) the negative verbal representation of attributes may direct people to focus on the regulation of emotions. These conjectures are consistent with the theoretical foundations of the present work.

Given the parsimonious behavior of model ACC and its agreement with model ACcE, it would be tempting to conclude that the ACC model is sufficient to capture the decision behavior. Under such framework, there would be no need to account separately for the role of emotions because they are highly correlated, becoming a redundant term in the model, hence unnecessary. However, it must be recalled that the choices to which the models were fitted contained only two attributes per alternatives favoring the additive compensatory structure and this way, results should be interpreted in this context until further validation is performed. In other words, the parsimonious behavior of model ACC might have been due to the particularities of the experimental task. Therefore, for choices with more attributes, where the compensatory decision process is less likely to occur, other models, in particular ACcE or ACncE may outperform ACC. The intermodel agreement of ACC and ACncE support this idea. A further point is that given the functional form and mathematical structure of the purely cognitive model performance, its parsimony could be attributable to the high level of correlation between weights and S.A.M. answers. This high correlation makes difficult the interpretation of how and when each model performs better. Such correlation may not be valid and realistic in other contexts (i.e., more attributes or variations in the hedonic connotations of options). Therefore, if the correlation between emotions and weights differed in diverse situations, the parsimony of the ACC model may be less clear. The predictive power of the ACC model in experiment 2 may be an extreme case where emotions and cognitions are highly correlated. A first test of this idea can be performed using data from experiment 1. In this experiment, the correlation of cognitive weights and emotions was less strong than that of experiment 2[15] (see tables 8 and 3). Even though data of experiment 1 is not suitable to fit the four models, it is enough to fit the ACC model. Results are displayed in table 14. The ACC model is fit to the data of experiment 1 using the same procedure used for the data from experiment 2. The columns correspond to the percentage of correctly predicted choices by treatment. Note that the column of experiment 2 is exactly the same column of the ACC model in table 12, for non depleted subjects. A test z of proportions with two sample of different size was used to assess the statistical significance of the differences. P values are reported in the last column.

Table 14. Predictive power of model ACC for experiments 1 and 2.

Treatment	Experiment 1	n	Experiment 2	n	p value
Verbal, A(+)	0.67	123	0.93	111	0.000
Verbal, B(+)	0.77	84	0.90	130	0.004
Numerical	0.65	189	0.92	132	0.000
Verbal, A(-)	0.70	117	0.88	116	0.000
Verbal, B(-)	0.69	117	0.87	115	0.000

Table 14 shows results that provide a preliminary answer of how well the ACC model would predict choices made when the correlation of cognition and emotion is low. As expected, there is a significant reduction of the ACC model's predictive power in all treatments. In addition, a comparison of table 5 and table 10, confirm that the role of emotions in choices was not as important in experiment 2 as it was in experiment 1. These

[15] I have no explanation about the reason why this correlation changed from one experiment to another. The only noticeable difference was the age differences of subjects, but I cannot provide any test of that.

results support the hypothesis that the performance of a purely cognitive model is positively related to the correlation level between cognition and emotional reactions. It follows that given its mathematical structure, the performance of a cognitive-affective type of model (e.g., ACncE) would not be affected by the correlation level. For that reason the cognitive-affective type of models have the potential to be valid in a wider set of decision situations than the purely cognitive ones. Thus, we need research using experimental contexts where the correlation between emotions and cognitions varies. Such research would validate and further explore the results of the present work.

CONCLUSION

The four cognitive-affective models of choice proposed and tested during the present research have provided several insights into the way people use and evaluate cognitive-affective information during the construction of preferences. They have also displayed a remarkable predictive power of actual choices. These insights shed light on some general properties of the way people construct their preferences using cognitive-affective information. The results that are directly traceable are the following:

1. Emotions and cognitions are interrelated, supporting the idea that people operate with cognitive-affective cues when determining their preferences. This result is consistent with the cognitive-affective models of thought like that of Bechara and Damasio (2005).

2. The performance of cognitive models of choice was influenced by the correlation level of cognitive weights and affective reactions. The stronger this correlation is, the better the cognitive model (i.e., ACC) performs.

3. Both emotions and cognition exert an effect on preferences, but cognition is more pervasive than emotion in the tasks studied here. The role of emotions varied as a function of (1) emotional valence, (2) depletion of self regulatory capacity and (3) the correlation level of cognitive weights and emotions.

Beyond these results, the findings of the present research suggest some ideas about the way people use emotions and cognitions when making decisions that are worth exploring and suggest the need for further investigation. Data suggest that it might be the case that people are able to choose the way in which they balance the combination of cognitive and affective information when making decisions. Pham (2004) suggested that people are able to monitor consciously the ecological validity of their feelings and the present research extends that notion providing details on how such monitoring activity takes place. Similarly, Wagard and Thagard (2004) explained that cognitive-affective information is generated by specific areas of the brain and then passed to the higher levels of reason where people actually make decisions. Luce, Bettman and Payne (1997) found that negative emotion makes decision processing more extensive and attribute-based. The present results extend that notion, introducing the idea that such extension of processing is the result of the use of procedural preferences on the way cognitive and affective information is combined and used during the construction of preferences. The following are several findings of the present work that build on those results.

1. People seem to develop procedural preferences over the way cognitive-affective information is used and processed. In particular, the lack of informational consistency among pieces of information (i.e., numerical and verbal attributes) complicates trade offs, generating a meta cognitive experience that triggers negative feelings towards the alternative. People seem able to identify this type of feeling and decide whether they use it or not as a cue for their preferences. This procedural decision depends on the valence of the information. When the trade off is performed over positive verbal information, people do not seem to use the meta cognitive negative feeling. On the contrary, if the verbal attribute is negative, it seems more likely that people use the negative meta cognitive feeling.

2. The level of self regulatory resources of the individual plays a salient role on the importance of meta cognitive feelings for preference construction. It was found that depleted participants tend to use this type of feelings more often than non depleted participants in the presence of negative verbal information. This implies that the need to regulate negative emotions triggered by meta cognitive aspects of decision making is strong enough to exert an effect on preferences, which is in turn affected by the ego depletion level of individuals.

3. People may feel more comfortable using the informative aspects of direct emotions (emotions triggered directly by the utility of an attribute) when information is consistent (purely numerical) and trade offs are “easy”. This explains the finding that in all experiments both emotions and cognitive weights were significant predictors of choices when they were expressed numerically. The verbal –

numerical manipulation was used following the idea that verbal content may help to infuse affect (e.g., Slovic et al, 2002a, 2002b Damasio, 1994) but it turned out that the procedural preferences of people may invalidate any additional feelings triggered by the type of representation employed.

4. Cognitions and emotions were found to be correlated but this correlation does not guarantee that both types of information are used as valid cues to construct preferences. Of the models proposed, the ACC model achieved the most parsimonious behavior in experiment 2. However its structure makes it insensitive to changes in the way people use cognition and affect and under low correlation of emotion and cognition, its performance is worsened. Under changing conditions, the most appropriate models to represent the actual choice process would be ACcE and ACncE. These models are sensitive to the cognitive-affective nature of the information that the brain produces for high level reasoning. Thus, these types of models capture the procedural preferences that people may employ when balancing the validity of cognition and affect.

A moment based representation of emotions in decision making

One of the objectives of this research is to provide a characterization of the role of emotions in decision making based on two major aspects. First, the process of decision making can divided in certain stages during which different emotions occur. Second, according to their source, emotions are of different nature and this determines to a great extent their role in the construction of preferences. In the following section and as a conclusion of this research, I develop a moment based characterization of the role of emotions in the construction of preferences. This conceptualization provides a deeper contextualization of the results obtained through the present research and offers a framework for the continuation of this investigation that has left many open questions.

In the literature review, I selected different types of research on the role of emotions in decision making according to their focus (e.g., mood, traits, anticipatory feelings, etc). I argue that to put those research findings in perspective (including those of the present research) it is necessary to develop a conceptualization of the different stages during decision making at which emotions of a different nature may exert an effect. Such stages can be divided in three. 1. Predispositional, 2. Evaluative and 3. Reflexive.

Predispositional stage

This is the period that precedes the decision. There are emotional factors that are present before people embark on the task of making choices. These emotional factors are related to mood (e.g., Isen, 1993) and affective traits of individuals (e.g., Peters and Slovic, 1994). The state of our emotions during the predispositional stage may determine, as explained in extant literature, the way information is processed and therefore the way we use emotions. In the present research, it was found that the level of self regulatory capacity is also a salient determinant of the way people use affective cues. This finding is located at the predispositional stage.

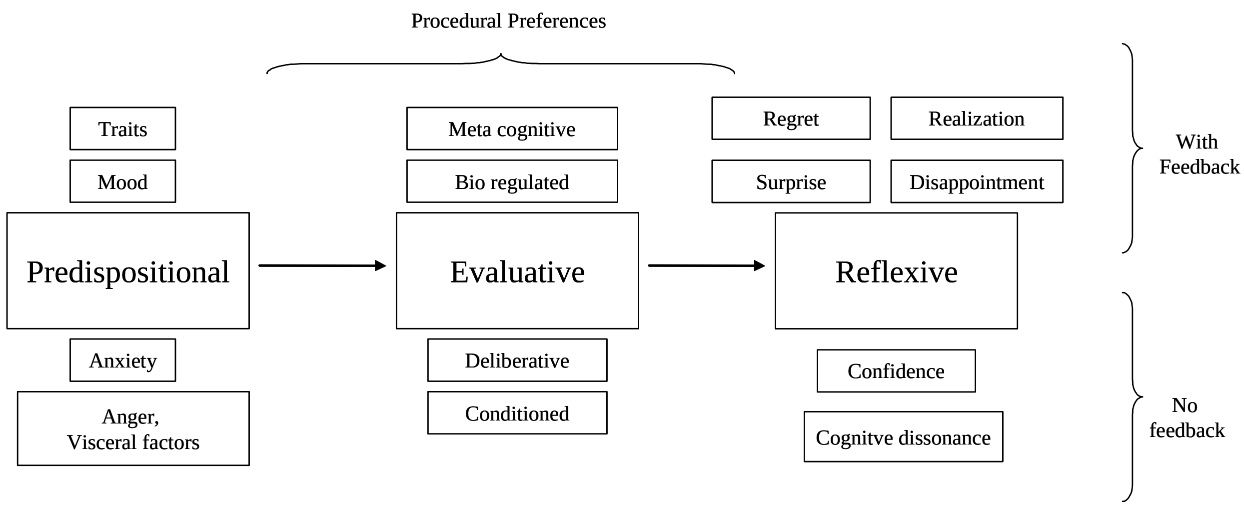
Evaluative stage

Once the individual starts the decision making process, she has to evaluate the cognitive and affective pieces of information and determine how these are valid cues for the construction of preferences. During this period, different types of emotions influence preferences. There are vivid emotions, triggered by the target, that act as information (e.g., Schwarz and Clore, 1996). They may be directly related to the attributes of options (e.g., liking the colour of a car) or the result of complex deliberations on the appropriateness of an alternative, triggering optimizing strategies regarding how people will feel when receiving feedback (e.g., Mellers and Ritov, 1999). The evaluative stage also triggers the problems of information processing (e.g., performing trade offs) and procedural preferences such as those found in the present research (e.g., consistency of information, regulation of negative feelings). In addition to these deliberative feelings, biological and conditioned emotions are also evoked during this stage.

Reflexive stage

This is the post choice stage. During this period, feelings are triggered by feedback, such that disappointment, regret, realization, surprise etc., affect the learning process of individuals and in some cases the construction of preferences for future choices that are recognized as similar. During this period, new conditioned feelings may be developed as well as deliberate procedural preferences over the use of emotions. However, in many cases, there is no feedback and the reflexive stage becomes more limited in terms of emotions, probably limiting these experiences to self confirmatory feelings derived from confidence and the tendency to avoid cognitive dissonance.

Figure 4. The three stage conceptualization of emotions in decision making



The results of the present research can be understood using the framework of the three stage process. I have provided a characterization of the way people develop procedural preferences for the way meta cognitive emotions are allowed to influence choices during the deliberative stage. These procedural preferences are reflected in the differential use of conditioned (direct effect of affective load of attributes), deliberative (evaluation of information consistency, regulation of negative emotions) and meta cognitive (affect derived from how hard (easy) it is to trade off verbal attributes) emotions. The depletion level of an individual is part of the predispositional stage, where emotional and cognitive states affect the cognitive-affective mixture of information that people later use during the evaluative stage. This research provides a description of how depletion modifies the way in which negative and positive affect of a meta cognitive nature is evaluated by participants, as valid cues to their preferences. In addition, the models provide an account of the emotional integration that takes place to determine the affective component of preferences.

The findings presented here provide a possible explanation of how such integration is performed in different ways as a function of predispositional variables and procedural preferences.

This research has taken a step forward in understanding the way people use emotions as a component of their preferences, by (1) providing a framework to organize the scattered results in the literature on affect and decision making (2) proposing and testing a formal conceptualization of the use of cognitive-affective information in the construction of preferences and (3) providing new insights into the use of some of the emotions that occur during the decision making process.

FUTURE RESEARCH

The results and proposals of the present research open several questions on the role of affect on decision making and provide a general framework for its analysis. There is a clear research agenda to extend the proposed models, and to study the different interactions between the emotions at different stages and the validity of the ACcE and ACncE models when these stages are manipulated. In the following section I propose some general directions for future research.

Components of the holistic emotional reaction

The results of the present research suggest that the affective reactions that occur during the decision process are the combination of different sources of affect. Pham (2004) recalls that there are emotions of at least three types: biological, conditioned and deliberative. These general categories of emotions can be traced to particular sub-processes of decision making. Some of these were uncovered by the present research.

For instance, I studied an affective reaction that is significantly related to a cognitive evaluation such as the subjective local weight assigned to an attribute that can be regarded as a conditioned emotion. This is the type of affective reaction that can be derived from an experiential system, where affect is conditioned through attachment to learned content and previous experience. But such emotion is just an element of a broader emotional evaluation, whose elements are not yet clear. The present work also produced results that made salient the presence of emotions of a meta cognitive nature, which are the result of deeper considerations about the procedural aspects of decisions. From the current results these were the only two types of emotions I was able to identify, but there is no reason to believe that these are the only ones that exert an effect during the decision process. Therefore, a future research agenda can be devoted to uncover the hidden structure of holistic affective reactions, disentangling the interaction of different types of emotions and their actual influence on choice. In particular, research should focus on the behavior and interaction of at least five types of emotions These are (1) biological, (2) conditioned and (3) deliberative (e.g., Pham, 2004; Lazarus, 1991) (4) meta cognitive (e.g, Luce et al, 2001) and (5) anticipatory (e.g., Mellers and McGraw, 2001). The focus of this research would be to trace these particular emotions to specific sub processes of decision making such that, performing trade-offs, cognitive anticipation of outcomes, meta-analyses of the choice context, etc.

Monitoring of feelings and procedural preferences

There was one phenomenon that appeared constantly through the present work: People seem to exert some degree of control over the cognitive-affective mix of information during the decision process. This could be a general principle of the way people use cognitive-affective information in determining preferences. It could be suggested that there are different types of cognitive-affective combinations that compete for attention, particularly if they are contradictory. Participants seem to be able to select the mix that better suits the decision process. The “How do I feel about it” type of reasoning (Schwarz and Clore, 1988) suggests that people perform an evaluation of their feelings in terms of what they mean and imply for the decision or judgment the person is involved in. This concept was taken further by Avnet and Pham (2004, cited by Pham, 2004) who speculated that such control of feelings is a meta cognitive activity that leads people to assess whether they should rely on emotions. The results of the present research lead to the speculation that such monitoring activity may lead people to develop well defined procedural preferences or “policies” about how they use their feelings during decision processes. These procedural considerations could be conscious or unconscious and can vary as a function of specific contexts or choice situations (e.g, information consistency). The elements and criteria of such procedural preferences and meta cognitive assessment of feelings could be the basis of a comprehensive research agenda. There are at least two hypotheses that should be explored, derived from the results of the present research. First, people let emotions flow and influence their preferences to a greater extent when the information about the choice alternatives is expressed in a consistent way. By the same token, the ambiguities of different types of information within the same set of alternatives (e.g., numerical and verbal) may lead people to rely more on cognition. Second, meta-evaluations of the decision situation, like the context in which the decision is embedded or the relevance of the goals related to the decision, may produce different combinations of cognition and emotion.

Validation of the models in a wider set of contexts

The behavior of the four proposed models is promising. They all reached high levels of predictive power. However, precisely because they were all so successful, more research is needed to test them in a wider variety of contexts and choice situations, particularly in the presence of more complex stimuli, (e.g., a larger number of attributes or uncertainty). The high performance of the ACC and ACcE models are arguably attributable to some particularities of the reported experiments. First, the task employed was the specific case of binary choice (two alternatives, A and B) described by only two attributes. The simplicity of this task may favor the use of a cognitive strategy in which performing trade offs was not very difficult for participants. Given this condition, a wide use of a compensatory decision process is not surprising. If this is true, the present experiments only capture one side of a complexity continuum in which simple straightforward choices are best captured by the ACC model, which has basically no difference from the Multiattribute Utility Theory "MAUT" (Keeney and Raiffa, 1976) model. In this case, adding emotions (correlated or not) could be unnecessary. However, at the other side of the complexity continuum, non compensatory processes and difficult trade offs can yield a totally different result. The ACcE and the ACncE models also achieved good levels of fit, but less parsimoniously. These models could be more appropriate in those circumstances.

The second particularity of the present data is the high correlation of cognitive weights and affective reactions (especially in experiment 2). This, made the performance of the ACC and ACcE models almost identical, rendering emotions an unnecessary complication of the ACC model. However, it is hypothesized that such correlation is a necessary condition for the superiority of the ACC model. The comparison of the performance of model ACC in experiments 1 and 2, reported in table 14, provides a basis for this hypothesis.

Thus, there are two main conditions that can be experimentally manipulated in order to assess the results. First, the stimuli complexity can be modified by changing three dimensions: (1) the number of alternatives and attributes, (2) the evaluability of attributes and (3) the information consistency. Second, different levels of correlation between cognition and emotions may be induced experimentally. There could be instances, with both simple and complex stimuli, where this correlation changes, increasing the use of alternative models. However, correlation may be affected by either situational variables or individual differences, or both. Additional research should be devoted to unveil the factors that influence the correlation of affect and cognition. The main hypotheses for the experiments to come are that (i) under complexity (as defined above) the emotional component of the decision models will become more important, and (ii) the correlational structure of cognition and emotion is positively associated with the use of cognitive models.

Validity of the multistage emotional decision process

I have proposed a multistage conceptualization of emotions during the decision process. By this notion I move from the measurement of holistic emotional reaction, to study the interplay of discrete emotions. Such a proposal opens an agenda on at least two fronts. First, research is needed to validate the three stages and the types of emotions that occur at each. Different type of emotions may be linked with specific stages. The hypotheses on these idea are shown in fig. 6 where specific emotions are linked with each of the three stages, moderated by the role of perceived feedback. (2) Second, the three stages are probably interdependent, and therefore, research will be needed to understand the internal structure and connections among the different stages. Two hypotheses on the interdependency of the emotional stages could be: (1) Changes in the predispositonal stage (e.g., variation on mood, or anxiety levels) exert an effect on the way cognitive-affective information is mixed during the evaluative stage, by altering the mixture of deliberative and conditioned emotions; and (2) Different types of feedback (e.g, exact vs. ambiguous) received during the reflexive stage, trigger specific emotions (e.g, surprise, disappointment) that are linked to anticipatory feelings. These emotions and how frequently they are triggered contribute to the development of stable procedural preferences which are determinant during the evaluative stage.

Ego depletion and use of emotions in the formation of preferences

It was reported in this chapter that participants whose cognitive capacities were depleted before the choice tasks, displayed a higher propensity to let their emotions influence their preferences. This result suggests that the role of emotions in decision making is sensitive to the momentary self regulatory power of people.

A research agenda that explores this phenomenon would mainly explore the following hypothesis: Depleted people rely more heavily on emotions to determine their preferences than non depleted people. This work should first confirm that the phenomenon occurs and then explore its magnitude. Such a research agenda includes the characterization of how the depletion effect interacts with other variations of the stimuli, such as complexity and repetition. For instance, I would explore how decisions made successively deplete the self regulatory capability such that, the last decisions are more emotionally determined than the first ones. This idea has important implications for consumer behavior.

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Appendix 1. Summary of attribute definitions

	Object	Attributes (A,B)	Scale	Dichotomy
1	Laptop Computer	Weight	Kilograms	Light/Heavy
		Screen Size	Centimeters	Wide/Narrow
2	Job	Training	Hours	Intensive/Scarce
		Workload	Hours Per Week	Reduced/Elevated
3	Car	Speed	Kilometers Per Hour	Fast/Slow
		Guarantee	Years	Extensive/Short
4	School	Tuition Fees	Thousands Of Euros	Costly/Cheap
		Position In Rankings	Ranking Position	Top School/ Unknown
5	House	Location	Minutes in Metro From Work	Near/Far
		Size	Squared Meters	Big/Small
6	Meal	Serving Time	Minutes	Quick/Slow
		Distance	Minutes Driving	Near/Far
7	Mobile Phone	Battery Duration	Hours	Short/Long Duration
		Size	Centimeters	Big/Small
9	Airticket	Connection Time	Hours	Long/Short
		How Old Is The Aircraft	Years	Old/New
9	Washing Machine	Capacity	Lbs. Of Clothes	Big/Small
		Time Employed To Complete A Whole Cicle	Minutes	Long/Short
10	Wooden Bookshelf	Capacity	Number Of Books	Big/Small
		Wood Duration	Years	High/Low Quality
11	Printers	Speed	Pages Per Minute	Fast/Slow
		Cartridge Duration	Total Pages	Durable/Limited
12	Savings Fund	Profitability	Interest Rate	High/Low
		Flexibility	Minimum Time of Money Availability	Flexible/Rigid

Appendix 2. Alphabetic sudoku

This game is played on a big square divided in 81 cells. These cells are grouped in nine smaller squares of nine cells each. The idea is to write numbers from 1 to 9 in the cells such that the nine numbers are contained within each group of nine cells and the nine numbers are contained in each row and column of the big square, which is 9 x 9. Some numbers are given to start, and the amounts of numbers given at the beginning as well as their position determine the difficulty of the game. For the purpose of the experiment, to make the game harder, and to avoid any priming on numbers, I replaced the numbers from 1 – 9 with letters from A to I. Below is the game as participants saw it and its solution. They had 10 minutes to write as many letters as possible. The best player wrote correctly 17 letters.

G	***E***	***F***			***A***	***I***		
			C					
D				***I***				***H***
		A						
I		***E***		***F***		***B***		***A***
						F		
H				***E***				***D***
					G			
		C	***D***			***E***	***B***	***I***

G	***E***	***F***	H	D	***A***	***I***	C	B
A	I	H	***C***	G	B	D	F	E
D	C	B	F	***I***	E	G	A	***H***
C	F	***A***	E	B	D	H	I	G
I	H	***E***	G	***F***	C	***B***	D	***A***
B	D	G	A	H	I	***F***	E	C
H	A	I	B	***E***	F	C	G	***D***
E	B	D	I	C	***G***	A	H	F
F	G	***C***	***D***	A	H	***E***	***B***	***I***

Appendix 3. Use of the product of valence and arousal scale.

This is equivalent to calculating the emotional “area” defined by the two separate emotional dimensions. The reason behind the use of the product instead of each variable separately is that the S.A.M. instrument is psychometrically effective to measure emotional reactions when at least these two dimensions are included. Bradley and Lang (1994) report using factor analysis that valence and arousal account for 24% and 23% of variance respectively. This way, using only one dimension would not capture the emotional reactions appropriately. Using the product, in addition, yields an emotional bipolar scale that is richer than the two separate dimensions. Arousal alone tells nothing about the direction of the emotion and valence alone says nothing about the intensity of the emotion. The product permits a better discrimination of participants. For example, two persons may report a value of 3 in valence, looking the same. However, in the arousal dimension, they may report a 1 and a 9 respectively, and the product of the two yield answers of 3 and 27, which are very different emotional reactions. That can only be revealed by virtue of the multiplication of scores. Note in figure 3, how the differences among 6 hypothetical participants are clearer using the combined score, than when separate scores are used, without altering the nature and direction of the differences.

Example of the comparison among emotional scores of Valence, Arousal and the combined measure.