Psychophysiological processes as a window into consumer decision-making

The role of visual attention, arousal, and valence for preference construction in discrete choice experiments

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Dipl.-Psych. Carsten Rasch

geboren in Tuttlingen

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Vorsitzende: Prof. Dr. Dorothea Alewell

Erstgutachter: Prof. Dr. Thorsten Teichert

Zweitgutachter: Prof. Dr. Mark Heitmann

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List of Abbreviations

adj. = adjusted

AFC = alternative-forced choice

ambi. = ambivalence

approx. = approximately

avg. = average

BDT = behavioral decision theory

BIC = Bayesian Information Criterion

BTL = Bradley-Terry-Luce model (Model for analysis of choice data)

CD = compact disc

cond. = condition

dBA = decibel A (A-scaled sound pressure level)

DCEs = discrete choice experiments

diff. = different

e.g. = exempli gratia (means: for example)

EBA = elimination by aspects

EDA = electrodermal activity

ESG = evaluative grid model

ESM = evaluative space model

et al. = et alii (translated: and others)

f.ex. = for example

FMCG = fast moving consumer good

GfK = Gesellschaft für Konsumforschung (society for consumer research)

H = hypothesis

Hz = Hertz

i.e. = id est (translated: that is)

i.i.d. = independent and identically distributed

IAPS = international affective picture system

IIA = independence of irrelevant alternatives

indiff. = indifference

LPT = line print terminal

LR-test = likelihood-ratio test

M = mean

ML = maximum likelihood

mm = millimeter

MNL = multinomial logit

ms = millisecond

mS/V = millisiemens per Volt

n = sample size

N = total sample size

n.s. = not significant

no. = number

Nobs = number of observations

OLS = ordinary least squares

p(x) = probability of feature x

p. = page

PAM = preferences as memory (as in PAM framework)

par. = parameter(s)

r = correlation coefficient

ρ = Spearman's rho (Rank correlation coefficient)

RUM = random utility maximization

SCR = skin conductance response

SD = standard deviation

SE = standard error

sec = second

TVA = theory of visual attention

V-AMP = versatile amplifier (produced by Brain Products)

vs. = versus (means: against)

will. = willingness

1 Introduction

Knowledge about preferences is of utmost importance when it comes to matching products, services, and communication with the needs of the consumer. This importance is illustrated and underpinned by the high failure rates of product development (see the report of the society for consumer research, GfK, 2006). Unfortunately, knowledge about consumers' preference is difficult to obtain, as preferences are to some degree constructed during measurement (Simonson, 2008b). Thus, preference elicitation is not always a reliable basis for preference prediction (e.g., Kivetz, Netzer, & Schrift, 2008). This work strives to deepen the understanding of the process of consumer decision-making with the help of psychophysiological methods in order to reach higher predictive validity in preference elicitation. Different approaches in matters of cognitive and affective processes are explored to identify constructive processes when consumers make choices.

1.1 Motivation and objective

A large amount of research has shown that a multitude of factors lead to the expression of constructed preference (Bettman, Luce, & Payne, 1998, 2008). According to Lichtenstein and Slovic (2006), it is well known that the interaction between human information processing and the properties of the relevant decision task influences preference construction. However, less is known about specific cognitive or affective processes, which have more or less impact on the constructive process. Instead of identifying decision characteristics that foster or reduce preference construction (e.g., Payne, Bettman, & Schkade, 1999b), this research focuses on the immediate cognitive and affective processes that entail more or less preference construction during decision-making.

Constructive cognitive and affective processes are measured with psychophysiological process measures when consumers make choices. Psychophysiological indicators enable the capturing of immediate cognitive and affective processes during decision-making. This advantage, compared with verbal or other subjective process measures (Poels & Dewitte, 2006; Wang & Minor, 2008), permits a closer look at memory processes taking place during preference decision-making (Weber & Johnson, 2009). This is crucial as memory processes are ultimately responsible for the expression of constructed or rather stable preference.

Consequently, psychophysiological indicators of visual attention, affective valence and arousal are captured and integrated in the estimation of utility within the mathematically sound discrete choice paradigm

(Louviere & Woodworth, 1983). The objective of this work is to establish a theoretical and methodological basis for disentangling constructed and stable preferences in discrete choice experiments by integrating psychophysiological process measures.

1.2 Structure and abstract of the work

At the outset, the theoretical basis of the phenomenon of constructed and stable preference is addressed (Chapter 2). Economic and behavioral perspectives on preference, as well as their eventual synthesis, get a closer look (Chapter 2.1). The economic perspective is well equipped with methodologies that measure preference that is traditionally presumed to be stable (Chapter 2.2). By contrast, behavioral research has clearly shown that preferences are easily changed, and basic cognitive processes might play a major role (Chapter 2.3). As cognitive processes are not easy to measure subjectively, this work utilizes psychophysiological indicators, namely visual attention, affective valence, and arousal.

The functions of visual attention in consumer decision-making are unpacked in Chapter 3. In an empirical study, N = 178 subjects took part in a discrete choice experiment about shoes with the parallel measurement of visual attention with mouse clicks (e.g., Cooke, 2006). Results show that gaze bias to the later choice indicates the strategy in use at specific stages of decision-making. Furthermore, a particular process, first gaze bias on the later chosen option, then on the option that does not get chosen, could indicate the construction of preference.

In a second empirical study (related to chapters 4, 5, and 6), affective valence and arousal were captured during discrete choice experiments for charity decisions, face decisions, and yogurt decisions (N = 49). Arousal was measured by skin conductance (Groeppel-Klein, 2005), and valence was measured by facial electromyography (J. T. Larsen, Norris, & Cacioppo, 2003).

The results of the integration of valence in choice models (Chapter 4) support the assumptions of the somatic marker theory (Bechara & Damasio, 2005), in which affect flags valence and thus stable preference. The joint consideration of positive and negative affect further reveals that, for difficult decision tasks, low ambivalence or indifference results in less constructed preferences (Nowlis, Kahn, & Dahr, 2002).

Related to arousal, which is addressed in Chapter 5, a more differentiated role is suggested. In cases with less prior experience with the particular decision task, arousal can function as a complexity-reducing mechanism that eventually leads to preference construction (Paulhus & Lim, 1994). If there is more experience with the decision task, it is suggested that arousal functions as a value marker, indicating the expression of stable preferences (Bechara & Damasio, 2005). Furthermore, the findings suggest that the assumption of an optimal level of arousal for stable preference expression is dependent on the difficulty of the decision task. An optimal level of arousal can lead to more stable preference expressions in demanding decision tasks.

The joint consideration of arousal and valence in Chapter 6 indicates that both processes might play a constituting role in preference expression. Furthermore, the combined analysis of arousal and valence yields the possibility to consider the effect of discrete affect programs (basic emotions) in preference decision-making (Loewenstein & Lerner, 2003). However, the heterogeneity of preference as well as affective patterns makes the interpretation of results explorative yet seminal.

In Chapter 7, the results of the studies are consolidated and led back to basic cognitive processes. Overall, the results promote the feasibility of disentangling constructed and stable preference by considering the immediate cognitive and affective processes in discrete choice experiments. The use of psychophysiological methods for preference research deepens our understanding of the basic psychological processes and might further open the window into consumer decision-making. Figure 1 provides a brief summary of this work.

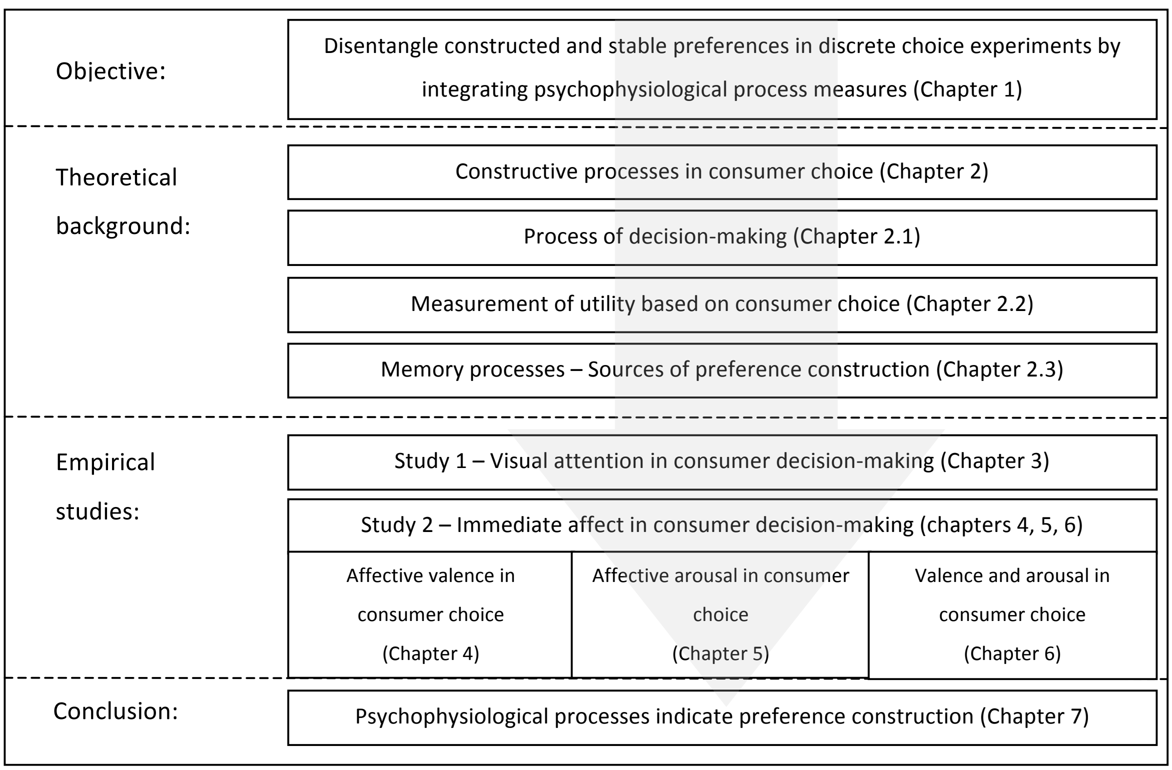


Figure 1 – Summary of this work.

2 Constructive processes in consumer choice

Imagine buying yogurt at the supermarket. When you arrive back home, you put the yogurt in the refrigerator. The next morning, you have it for breakfast, but suddenly you realize you actually do not really like this yogurt. If this has ever happened to you (maybe with other products), you might have been a victim of spontaneous preference construction, which is a temporary change of otherwise stable preferences. A frequently occurring introduction to articles of behavioral decision theory bolsters this possible everyday experience: "There is growing consensus that preferences are typically constructed when decisions are made, rather than retrieved from a master list of preferences stored in memory." (Simonson, 2008a, p. 155). As there is already a vast amount of research showing that preferences are constructive (Lichtenstein & Slovic, 2006), this work strives to set a theoretical and methodological basis for evaluating the construction of preference with psychophysiological process measures in discrete choice experiments.

2.1 Decision processes as chance for preference elicitation

Companies strive to develop and produce or provide exactly what their customers desire. This might sound easy, but it is very difficult to achieve. The big dream of every producer or service provider is to serve the needs of as many customers as possible, as this might assure substantial revenue. It is not easy to make this dream come true, considering how quickly customers' preferences can (and often do) change. Newly launched products suffer from notoriously high failure rates, which often reach 50% or higher (GfK, 2006; Ogawa & Piller, 2006). Not surprisingly, reliable knowledge about the customer's needs is of great importance, but it is rarely attained when a new product is in development (Henard & Szymanski, 2001; Ogawa & Piller, 2006). This insight leads us to focus on the nature of preference and how to measure it: Are preferences inherently unstable, quickly changing constructs? Based on the latest research (e.g., Kivetz et al., 2008), the quick and wholly unsatisfying answer would have to be: sometimes, and sometimes not! This dissertation will provide insights that deepen the understanding of the nature and the measurement of consumer preferences with the support of psychophysiological process indicators. The objective is to clarify why and when quickly changing or stable preferences are measured.

2.1.1 Behavioral and economic perspectives on preference

For the interested market researcher, in the best case, preferences would be "[…] stable preference components or dispositions that are assumed to reside within a person over an extended period" (Kivetz, Netzer, & Schrift, 2008, p. 180). In the worst case, preferences would be constructed on the spot during elicitation, changing every now and then, depending on elicitation context. For example, Bettman, Luce, and Payne (1998, abstract) state: "We argue that consumer choice is inherently constructive." These two perspectives on the nature of preference mirror the two main research streams interested in preference measurement: economics and behavioral decision theory (BDT). Whereas the standard economic view relies on a "master list of preferences" that is used by individuals to maximize the expected utility of given options (origins: von Neumann & Morgenstern, 1953), behavioral decision research clearly indicates that this assumption is not sufficient (Tversky & Kahneman, 1974).

Behavioral decision research proceeds by testing the descriptive adequacy of normative economic theories of judgment and choice. In doing so, it makes substantial use of psychological concepts in general, and cognitive mechanisms in particular (Payne, Bettman, & Johnson, 1993). The most prominent alternative to the standard economic perspective is the prospect theory (Tversky & Kahneman, 1981), which asserts that people evaluate outcomes as gains and losses resulting from a comparison with a context-dependent reference point. Besides this Nobel Prize-winning concept (for which Daniel Kahneman received the prestigious award in 2002), a large body of research shows that preferences are mostly constructed during the decision process (Bettman et al., 1998; Lichtenstein & Slovic, 1971, 2006).

That preferences can be influenced (e.g., through persuasion, or advertisements) is not the new insight provided by BDT. The notion of preference construction goes well beyond influence, suggesting that preferences are so pliable that they are often largely created by the context, elicitation method, and description of options (e.g., Lichtenstein & Slovic, 2006).

Although the archeological (economic) and the architectural (BDT) perspectives on preference elicitation seem incompatible with each other, a synthesis becomes apparent. Both perspectives assume a relatively stable basis of preference construction, whether one calls it disposition, or in the language of choice modelers, a "meta-attribute" that is used to eventually construct concrete preference expressions for products and product attributes (Kivetz et al., 2008, p. 181). Simonson (2008b) illustrates this notion with an example and argues that consumers might have a strong disposition toward lifelike gaming experiences (a meta-attribute) rather than an inherent preference toward the Nintendo Wii's motion-sensitive remote (specific product attribute). Thus, dispositions might underlie preferences that emerge when products are encountered. Whereas the disposition is likely to be relatively stable, its realization as a preference expression is susceptible to changes in the local contextual and temporal environment (see the fictional illustration in Figure 2). On top of stable preference, contextual and / or temporal conditions could generate fast and local modifications of consumers' preferences.

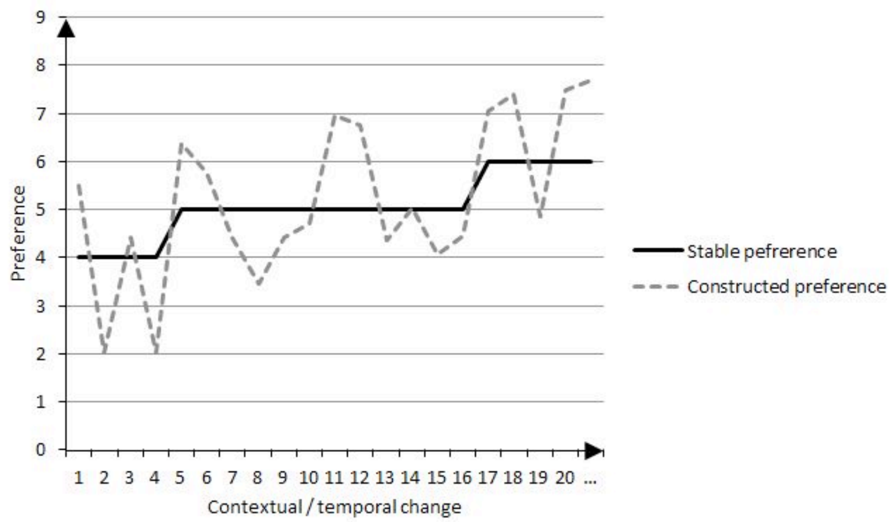


Figure 2 – Fictional illustration of stable and constructed preferences (based on Kivetz, Netzer, & Schrift, 2008)

Consistent with this thought, violations of the notion of a "master list of preferences" rely on the existence of stable preference. For instance, the asymmetric dominance effect (Huber, Payne, & Puto, 1982) can only occur when the consumer already has an ordinal preference order that can be influenced by a decoy option. The asymmetric dominance effect, also labeled "decoy effect" (Huber et al., 1982), describes the phenomenon that preference changes when a specific new option is introduced to the decision-maker. If the newly introduced decoy option is inferior in all respects to one option - which then dominates - but only in some respects to another option, the initial preference of the decision-maker is likely to change in favor of the now dominating option. Without a stable disposition to prefer some attribute levels over others this effect would not occur in such a consistent manner (Pettibone & Wedell, 2000).

A large body of research now acknowledges that some choices are constructed, but not all of them (Bettman et al., 2008; Simon, Krawczyk, Bleicher, & Holyoak, 2008; Simonson, 2008b; Warren, McGraw, & Van Boven, 2010). For this synthesis, the challenge that logically follows is to test and falsify the proposition that a particular choice was driven by stable rather than constructed preferences (Kivetz et al., 2008). In order to tackle this challenge, it is necessary to understand the complexity of the constructive nature of preference, which will be the objective of the following section.

2.1.2 Constructive nature of preference

Contrary to the growing acknowledgement that preference is constructed to some degree (Simonson, 2008b), the basic assumption of rational (economic) theories of choice is the principle of invariance (e.g., Tversky, Sattath, & Slovic, 1988). Following the principle of invariance, preferences should not depend on a description of options, or the method of elicitation (Slovic, 1995). McFadden further elaborates this notion by summarizing the normative stance as follows: "The standard model in economics is that consumers behave as if information is processed to form perceptions and beliefs using strict Bayesian statistical principles (perception-rationality), preference are primitive, consistent and immutable (preference-rationality), and the cognitive process is simply preference maximization […] (process-rationality)" (1999, p. 75). Clearly, there is a great deal of irony in this citation, and substantial research has already falsified these assumptions of rationality (Lichtenstein & Slovic, 2006).

Especially the assumed perception-rationality, which implies descriptive invariance, is strikingly rejected by research. Tversky and Kahneman (1981) established the basis for further research on descriptive invariance with their famous "Asian-disease-problem" (a basis for prospect theory). In this paradigm, two disease control programs are offered to decision-makers that vary in their semantic frame ("lives saved" versus "deaths prevented"), while the absolute impact of the two suggested programs is identical. The positive "lives saved" framing often induces risk aversion; the negative "deaths prevented" framing often leads to risk taking, which ultimately results in preference reversals. The term "decision frame" is broadly defined and refers to the selective perception of meaning associated to words, pictures, phrases, in general, the context of decision-making. To make it more complicated, both the context and the characteristics of the decision-maker can (partly) control the adoption of a certain frame (Tversky & Kahneman, 1981).

Mandel and Johnson (2002) showed in their research how characteristics of the decision-maker, and very subtle changes in the context influence choice. They used a priming approach to change decision-makers' accessibility to information stored in memory (comparable to framing). The prime consisted of different wallpapers of online shops. Clouds in the background should prime comfort, whereas coins in the background should prime price sensitivity. Furthermore, they measured the participants' familiarity with the presented products (sofas) as characteristic of the decision-maker. Results showed that both experts and novices were influenced by the primes and changed their choices accordingly. Participants with cloudpriming were likely to choose the more comfortable sofa, whereas participants with penny-priming were likely to select the more reasonably priced seating. Most interestingly, this impact works in different ways for novices and experts. For novices, the primes influence the external information search (measured with mouse-click data) during decision-making and therefore change choice behavior. For experts, external search does not change between different primes, yet choice behavior still changes. In order to understand the effects of primes more comprehensively, Mandel and Johnson (2002) point to the importance of further research on memory-based processes that influence choice.

This example illustrates that the complicated interaction between the context (e.g., wallpaper) and the characteristics of the decision-maker (e.g., familiarity) could be resolved by a closer look at cognitive processes during decision-making.

The regard of cognitive processes during decision-making is considered the link between perception and preference. McFadden's (1999) ironic view on the problems of the normative stance of decision-making (perception, preference, and process rationality) could be resolved by taking all three concepts into account when analyzing decision-making. Behavioral decision theory supports this notion: Bettmann et al. (1998) consider their "constructive choice framework" as an observation of problem representations that arise as a result of the structure of the task. They conclude that the "principles governing how representations are formed" (p. 208) should receive more attention in future research. The next subsection presents the state of research on the integration of perception, cognition, and the outcome of decision-making.

2.1.3 Process of preference decision-making

Perception, cognition, and outcome in the process of decision–making are tightly intertwined. Nevertheless, an attempt of a disjunctive perspective might serve deeper understanding. In line with this notion, Tversky and Kahneman (1986) consider mental effort (cognition) important but basic perceptual processes even more important. Basic perceptual processes are assumed to govern the cognitive representation of decision problems. For example, Tversky and Kahneman stress that "framing effects resemble visual illusion more than computational errors" (Tversky & Kahneman, 1986, p. 260).

Montgomery (1983) considers decision-making a tight mash-up of cognition and perception. In this view, decision-making is a sequence of structuring and restructuring activities, in which a multitude of compensatory and non-compensatory rules are used to restructure the decision problem (Montgomery, 1983; Svenson, 1999). The (re)structured decision problem representation based on perception and cognition is the key concept in preference construction.

Interesting empirical support for the high impact of perceptual processes on constructive processes comes from research on the role of incentives in decision-making (Payne, Bettman, & Johnson, 1992). If the only factor influencing decision-making was cognition (or mental effort) then one would expect violations of the maximizing principle to be eliminated by proper incentives. Empirical results suggest that constructive errors in preferential choice persist, even in the presence of monetary pay-offs (Grether & Plott, 1979; Kahneman & Tversky, 1984). Usually, incentives cause decision-makers to work longer on the presented problems, but without an increase of accuracy. Paese and Sniezek (1991) report that increased effort leads to increased confidence in judgment, without increased accuracy. Payne, Bettman, and Johnson (1992) provide the following summary: " ... for incentives to lead to a strategy shift, a better strategy must be available." (p. 115). If the decision-maker does not have a well-developed model of the task, which is usually the case, the possibility of doing better in a normative stance, will not be detected (Brehmer, 1990, p. 267).

There are several ways the integration of cognition (cost / benefit trade-offs) and perception could take place in the process of (re)structuring a given decision problem. Tversky, Slovic, and Kahneman (1990) suggest a cycling between mental effort and perceptive processes, both carried out with equal exertion, that is present during the whole duration of decision-making. Payne et al. (1992) suggest that perception is especially relevant in the first moments of decision-making (during the noticing stage), which is followed by determining what to do with the noticed aspects, i.e. the mental effort. In this view, perceptual processes govern the assessments of costs and benefits for any decision strategy that is available. That means perceptual processes determine how the decision problem is represented and framed (Payne et al., 1992).

Independent of the question which aspect (perception, cognition) dominates the other, it is acknowledged that both play a role in the process of decision-making that should not be discounted. This also means that both perception and cognition might influence the construction of preference. Given that either data driven-aspects (e.g., color, size of an alternative) or goal-driven aspects (e.g., prior experiences with alternatives) affect the constructive process during decision-making, a new level of complexity is added to the research on preference construction.

Johnson et al. (2008) make clear why there are still only a few models that start to account for perception and cognition in decision-making (e.g., Decision Field Theory, Roe, Busemeyer, & Townsend, 2001): Process models deserve process data, which is not easy to acquire, and process models are easily falsified. Models that rely only on inputs (aspects of decision task / context) and choices are not well specified and not easily falsified (Otter, Allenby, & Van Zandt, 2008). A falsified process model (priority heuristic, for example; Brandstatter, Gigerenzer, & Hertwig, 2006) is scientifically more important than a hard to falsify outcome model. Owing to their specificity, errors in prediction are very telling for future research.

By contrast, Einhorn, Kleinmuntz, and Kleinmuntz (1979) argue that simple linear regression models are capable of capturing the cognitive process of decision-making, but only additional process data can help develop and resolve issues raised by regression results. Aspects that regression analysis resembles are trade-off and redundancy effects, which are captured in the regression weights, as well as inconsistency and random error as result of cognitive limitations (Einhorn et al., 1979). This more or less superficial isomorphic representation of decision-making is to be enriched by specific process data in order to rigorously test hypotheses about perceptional and cognitive processes in decision-making. Einhorn et al. (1979) suggest that “regression models may conveniently serve as baselines for comparing various process-models” (p. 482), a suggestion that will be followed in this work.

In sum, research points out that preference is constructive to some extent, due to the multitude of perceptive, cognitive and possibly very important yet neglected affective processes that influence and constitute decision-making (Lichtenstein & Slovic, 2006; Slovic, 1995). It is important to pay attention to the constructive nature of preference, especially for the measurement and prediction of preference. A deeper knowledge about the psychological processes during preference decision-making could help to disentangle the stable from the possibly constructed parts of expressed preferences. Here, psychophysiological process measurement comes into play. Psychological processes measured by physiological process-measures could indicate the relative weight of stable or constructed preference in the revealed preference (Simonson, 2008b, p. 164). The advantages and correct utilization of psychophysiological methods shall be discussed in the respective method chapters (chapters 3.5.1, 4.7.1, 5.4.1, and 6.3.1).

Psychological constructs that resemble perceptual, cognitive, and affective processes are discussed in the following chapters, as well as their use in already conducted decision-making research. For a deeper understanding of the constructive process of decision-making, decision research profits from other areas of psychology. Especially, research on memory, visual attention, and affect are fruitful additional perspectives on the usage and the (re)structuring of information during decision-making (Mano, 1994; Weber & Johnson, 2009). Before we take a closer look at these constructs and their potential use in preference elicitation, the criterion construct, utility, and its measurement must first be disentangled.

2.2 The concept of utility

Preference is strictly defined as the selection of a product / service over some other product / service (Warren et al., 2010). Preference is therefore an explicitly observable behavior that allows inferring for the utility causing this behavior. Although the utility concept has received criticism (circular concept, see Robinson, 1962), it is acknowledged as a preference-causing construct by more behavioral decision researchers (Simonson, 2008a). The exciting part of the inference from preference to utility is how it is done. Early observations of human decision behavior already suggested that a deduction from preference to strictly monotonic rising linear utility does not adequately describe decision behavior.

The concept of utility derived from a simple observation that was made by a number of mathematicians over the course of the 18th century. In a roulette example, Blaise Pascal would have argued that humans, if rational, should be indifferent to a bet on red (low risk, low win, 1:2) and a bet on a number (high risk, high win, 1:36). Empirically, however, 18th century scientists observed that humans were not indifferent: When asked to choose between two bets of equal expected value but with different probabilities of winning, humans routinely select the lower risk bet. This aversion to risk was formally characterized within decision theory by the Swiss mathematician Daniel Bernoulli (1954 [1738]) using a concept he called utility. Rational decision-makers are, Bernoulli argued, naturally cautious. Whenever they have to choose between two options of equal expected value that present different levels of risk (and hence must offer different levels of reward if they are to have the same expected value), decision-makers always prefer the lower risk option (see also the St. Petersburg paradox, e.g., Martin, 2004). It was as if, when the expected value is computed, the higher rewards (necessarily associated with higher risks) had less influence on decision-making than expected, and the value of a gain to the decision-maker seemed to grow more slowly than the numerical value of the gain. Placing this example within the framework of Pascal's expected value theory (Pascal, 1670), Bernoulli chose to include risk sensitivity in models of decision-making by suggesting that humans do not directly multiply likelihood with gain but instead multiply likelihood with a concave function of gain called utility. It is the product of this quantity and likelihood, a product known as expected utility, which Bernoulli argued represents the decision variable employed when efficient choices are made. For further information on this topic, see Kreps (1990) for an overview of expected utility theory pertaining to economics, or Glimcher (2003) for an overview related to neurobiology.

Von Neumann and Morgenstern (1953) posted axioms sufficient for computing utility, based on observable decision behavior. The von Neumann-Morgenstern expected utility is based on a set of assumptions. The most basic assumption is that the world of preferred objects consists of probability distributions that refer to attributes defining the objects. For example: You have a one-third chance to select a yogurt with strawberry taste and low calories, but a two-thirds chance to select a yogurt with strawberry taste and high calories. If a consumer has a preference for one of the yogurts, with the two probability distributions being *p(strawberry / low calories)* and *r(strawberry / high calories)*, then there is an immediate insistence on two properties: asymmetry and negative transitivity. A preference is asymmetric when *X* is preferred to *Y*, and *Y* is not preferred over *X*, which means *Y* has to be more disliked than *X*. Negative transitivity of preference is achieved if *X* is preferred over *Y,* and *Y* is preferred over *Z*, and *Z* is not preferred over *X*.

Unfortunately, these mathematical foundations of expected utility do not consider the psychology of human beings (see Tversky & Kahneman, 1981 for examples when these assumptions are falsified). The mathematical foundations serve to describe what happens, but not why it happens (as most concepts in economics did, Kreps, 1990, p. 4).

Another assumption often made in expected utility research is labeled the completeness assumption, which takes ivory tower thinking to the extreme. This assumption proposes that a customer knows all the facts (probability distributions) contributing to the decision (e.g., Friedman & Savage, 1948). The first one to challenge this rather optimistic assumption was R. D. Luce, who discovered that decision-making is dealt with quite locally, not with a representation of all the relevant probability distributions that are possible (R. D. Luce, 1959).

2.2.1 Basic notions on utility measurement

Luce's approach to a locally derived decision utility is based on the work of psychometrician L.L. Thurstone (Thurstone, 1928, 1929). His "law of comparative judgment" posits a psychological continuum as a basis for comparisons of a series of stimuli. In the psychophysical tradition, Thurstone first experimented with weights, luminance, and volumes as stimuli, but soon extended his research to attitudes and values (1929). In one experiment, statements about capital punishment served as stimuli, and people had to judge which of two statements expressed a stronger positive or negative attitude. The basic idea is that a series of pairwise comparisons allows scaling stimuli based on the subjectively perceived "weight" of presented stimuli. The law of comparative judgment also posits that the discriminal dispersion of a stimulus is normally distributed with a standard deviation of one. That means if two stimuli are compared very often (> 30), their relative scale deviates around a "true" value, and a difference can be calculated. When replacing the normal density with a simple logistic function, the structure of the Bradley-Terry-Luce model (BTL) is attained (R. A. Bradley & Terry, 1952; R. D. Luce, 1959). Luce's axiom is already incorporated into the BTL model, which states that choice of an option always depends on the other options in a choice set.

The probability to select an item *i* of a pool of *j* items is given by: $p(i) = w_i / sum(w_j)$, in which *w* indicates the weight of an item.

The BTL model already acknowledges that decisions are made in a local set of options, and that choice is an adequate means to measure the utility behind decision outcomes. This notion is represented in the mathematical form of the BTL model: $p(x|y) = u(x) / u(x) + u(y)$, where *x* and *y* are the choice options, *u* is the according utility and *p* is the choice probability. Departing from the law of comparative judgment, the BTL model does not include an error term that allows for an unsystematic deviation of the scaled option utilities.

Jacob Marschak (1960) introduced Thurstone's work in economics and called this approach random utility maximization (RUM). Based on this introduction, Luce's groundbreaking work is the development of an axiom that simplified the experimental collection of choice data by allowing multinomial choice probabilities to be inferred from binomial choice experiments (R. D. Luce, 1963). The independence of irrelevant alternatives (IIA) axiom states that the ratio of choice probabilities for alternatives *i* and *j* is the same for every choice set *c* that includes both *i* and *j*.

McFadden (1974) completed the model to the conditional logit, also called multinomial logit model, in which multiple choices can be considered in a RUM-perspective (fixed utility multiple choice models were developed earlier; Luce, 1959). The utility in this model is composed by a systematic utility assigned to observable attributes of an option, and an unsystematic error due to unobservable (unobserved) factors.

Besides the sound mathematical basis for discrete choice analysis (the law of comparative judgment), there are further arguments for the observation of choice, and not ratings, in order to draw the conclusion that utility probably guides decision behavior.

Human beings make relative rather than absolute judgments. A number of authors have suggested that when humans and animals make decisions they consider the relative expected utility of each available action rather than the absolute expected utility of each action (e.g., Glimcher, Dorris, & Bayer, 2005). These rather experimental findings yield face validity, as consumers very likely do not stand in front of the yogurt shelf in the supermarket and rate one yogurt independently of another yogurt (absolute judgments); instead, they choose from a set of presented yogurts (relative judgments).

A further argument for choices as a means for preference measurement is that choices induce a trade-off. When making a choice, it is not possible to judge two or more options as equally likeable (as in ratings). Thus, choices very likely reveal non-ambiguous judgments.

When observing choices, the price to pay is low information content (choice vs. no choice) and a rather high number of evaluations to be made for valid analysis. For example, choice sets with two options have *(n*(n-1))/2* paired comparisons, whereas a rating procedure would have just *n* evaluations. The relatively high number of judgments carries the danger of a growing lack of concentration in the course of survey completion, which is discussed controversial (Adamowicz, Boxall, Williams, & Louviere, 1998; Lancsar & Louviere, 2006; Phillips, Johnson, & Maddala, 2002).

In summary, the measurement and analysis of choices for utility measurement is grounded in the random utility concept, in which the utility of a product is interpreted as a latent random variable. It is not assumed that all determining components of utility are or can be observed. The utility of products is therefore composed of a deterministic and a stochastic component. Contrary to alternative means to measure utility (rating scales, dollar metric, etc.), its measurement with choices is considered the best fit with actual decision behavior. The discrete choices of respondents are used to determine preference and subsequently to deduce particular utilities of attribute levels of presented products. The following subsection will put the ideas formulated above in a concrete operational setting in order to deepen the understanding of discrete choice experiments.

2.2.2 Measurement of utility

Discrete choice experiments resemble a decompositional method for preference analysis (Louviere & Woodworth, 1983). Although only nominal data is examined (choice vs. no choice), DCEs allow determining particular utility components that bundle in decision options. DCEs estimate utility components as well as choice probabilities of options. Therefore, two functions are necessary: One combining utility components to the total utility of an option, and another combining the total utility of an option with its choice probability.

The total utility is composed of a deterministic and a stochastic component:

(1) $$u_{h,i} = \psi\left[v_{h,i}\left(x_{i,j,m}, \beta_{h,j,m}\right)\delta_{h,j}\right] \qquad \forall h \in H, i \in I$$

$u_{h,i}$: Total utility of the *i*-th option for the *h*-th respondent

$\Psi(\bullet)$: Link function that combines the utilities of $|J|$ attributes and their attribute levels $|M_j|$

$v_{h,i}$: Deterministic part of the total utility of the *i*-th option for the *h*-th respondent

$x_{i,j,m}$: Value of the *m*-th attribute level regarding the *j*-th attribute at the *i*-th option

$\beta_{h,j,m}$: Utility parameter of the *m*-th attribute level regarding the *h*-th respondent

$\delta_{h,i}$: Stochastic part of the total utility considering the *i*-th option and the *h*-th respondent

A linear-additive, compensatory link function of the combined attribute judgments (total utility $u_{h,i}$) is assumed:

(2) $$u_{h,i} = v_{h,i} + \delta_{h,i} \text{ with } v_{h,i} = \sum_{j \in J} \sum_{m \in M} v_{h,i,j,m} \qquad \forall h \in H, i \in I$$

$v_{h,i,j,m}$: Utility of the *m*-th attribute level regarding the *j*-th attribute of the *i*-th option for the *h*-th respondent

The function that describes the utility of a particular attribute $v_{h,i,j,m}$ is modeled as a compendium of the particular attribute utilities, also called part-worth model:

(3) $$v_{h,i,j,m} = \beta_{h,j,m} \cdot x_{i,j,m} \qquad \forall h \in H, i \in I, j \in J, m \in M_j$$

$\beta_{h,j,m}$: Utility parameter of the *m*-th attribute level regarding the *h*-th respondent

$x_{i,j,m}$: Value of the *m*-th attribute level regarding the *j*-th attribute at the *i*-th option with $x_{i,j,m} = 1$, if the *i*-th option possesses the *m*-th attribute level of the *j*-th attribute, 0 if not.

The stochastic component of the utility function is not directly observable and can be influenced by unobserved attributes, unobserved heterogeneity, measurement error, or model misspecification (Zwerina, 1997, p. 25). It is assumed that stochastic utility components are independent and identically distributed (i.i.d. assumption).

Based on the assumption that respondents maximize utility, the *i*-th option is chosen if it is experienced as the most beneficial compared with all options.

(4) $$u_{h,i} > u_{h,i`} \qquad \forall h \in H, i, i' \in I \text{ and } i' \neq i$$

This relationship can also be written as:

(5) $$\sum_{j \in J} \sum_{m \in M_j} v_{h,i,j,m} + \delta_{h,i} > \sum_{j \in J} \sum_{m \in M_j} v_{h,i',j,m} + \delta_{h,i'} \qquad \forall h \in H, i, i' \in I \text{ and } i' \neq i$$

Thus follows:

(6) $$\sum_{j \in J} \sum_{m \in M_j} \left(v_{h,i,j,m} - v_{h,i',j,m} \right) > \delta_{h,i'} - \delta_{h,i} \qquad \forall h \in H, i, i' \in I \text{ and } i' \neq i$$

As the difference between the stochastic utility components ($\delta_{h,i}$, $\delta_{h,i'}$) is not directly observable, the choice behavior of an respondent *h* can be described only in terms of probability.

(7) $$P_{h,i} = \Pr ob(u_{h,i} > u_{h,i'}) \qquad \forall h \in H, i, i' \in I \text{ and } i' \neq i$$

$P_{h,i}$: Choice probability for the *i*-th option of the *h*-th respondent

The choice probability of the *i*-th option is therefore not determined by the total utility, but by the utility difference of at least two options. Based on the i.i.d. assumption, the stochastic components are assumed to be Gumbel distributed. Compared with normal distribution, Gumbel distribution facilitates parameter estimation and resembles the normal distribution very closely (Hensher & Johnson, 1981). As more than two options are usually considered in decision situations, a polytome decision has to be modeled. The multinomial logit (MNL) model resembles an estimable description of a polytome decision situation with i.i.d. assumption:

(8) $$P_{h,i} = \frac{\exp\left(\sum_{j \in J} \sum_{m \in M_j} \beta_{h,j,m} \cdot x_{i,j,m}\right)}{\sum_{i' \in C_a} \exp\left(\sum_{j \in J} \sum_{m \in M_j} \beta_{h,j,m} \cdot x_{i',j,m}\right)} \qquad \forall h \in H, i \in C_a \text{ and } C_a \subseteq I$$

C_a: Index for options in *a*-th choice set

The MNL model describes the choice probability as a non-linear relationship between the utility of an option and the utilities of the other option(s). An S-like form describes the relationship between choice probability and the estimated utility of an option. This model also resembles the independence of irrelevant alternatives (IIA) attribute. The advantage of the IIA attribute is the independence of options regarding the choice probability of an option. Options that are not chosen can be eliminated or added in the analysis of choice, which facilitates the parameter estimation. A disadvantage is the possibly implausible assumption that unobserved attributes of options are independent of each other. This goes along with the implausible assumption of no learning effects in subsequent choices. The violation of the IIA attribute by correlated stochastic components leads to systematically biased estimation results. Relaxation of the IIA attribute can be achieved by random parameter models (Train, 2006).

The estimation of parameters cannot be pursued by OLS estimation, as the nominal low content information (choice vs. no-choice) would violate the specific requirements. Therefore, the maximum-likelihood (ML) method is used to estimate the utility parameters (see Bunch & Batsell, 1989 for a comparison of ML method with other estimation methods). The basic notion for the estimation is that observed choices are influenced by different utility parameters of the particular attribute levels. The estimation method searches for the set of utility parameters that resemble the observed choices as much as possible. Utility parameters are systematically identified by the ML method. A pre-condition is that observed choices constitute independent random realizations of their population. The MNL model for choice probability constitutes the function that is to be maximized. As choices are assumed to be independent of each other, a multiplicative combination of the likelihood functions of different respondents is feasible:

(9) $$L(\hat{\beta}) = \prod_{h\in H}\prod_{a\in A}\prod_{i\in C_a}\hat{P}_i^{d_{h,i,a}} = \prod_{h\in H}\prod_{a\in A}\prod_{i\in C_a}\left[\frac{\exp\left(\sum_{j\in J}\sum_{m\in M_j}\hat{\beta}_{j,m}\cdot x_{i,j,m}\right)}{\sum_{i'\in C_a}\exp\left(\sum_{j\in J}\sum_{m\in M_j}\hat{\beta}_{j,m}\cdot x_{i',j,m}\right)}\right]^{d_{h,i,a}} \xrightarrow{\max}$$

L: Likelihood function

$\hat{P}_i$: Estimated choice probability for the *i*-th option

$\hat{\beta}_{j,m}$: Estimated utility parameter of the *m*-th attribute level in the *j*-th attribute

$d_{h,i,a}$: Binary variable for the choice of the *i*-th option from the *a*-th choice set by the *h*-th respondent, which is 1 if option is chosen, 0 otherwise

H: Index for respondents

A: Index for choice sets

C_a: Index for options in the *a*-th choice set

The values of the likelihood functions lie between 0 and 1. As these values are very small and therefore difficult to interpret the function (9) is logarithmized. The resulting values are negative and lie between [-∞; 0]. Logarithmizing does not affect the estimation of parameters.

(10) $$\ln L(\hat{\beta}) = \prod_{h\in H}\prod_{a\in A}\prod_{i\in C_a} d_{h,i,a}\ln\hat{P}_i = \prod_{h\in H}\prod_{a\in A}\prod_{i\in C_a} d_{h,i,a}\ln\left[\frac{\exp\left(\sum_{j\in J}\sum_{m\in M_j}\hat{\beta}_{j,m}\cdot x_{i,j,m}\right)}{\sum_{i'\in C_a}\exp\left(\sum_{j\in J}\sum_{m\in M_j}\hat{\beta}_{j,m}\cdot x_{i',j,m}\right)}\right] \xrightarrow{\max}$$

Function 10 only depends on the utility parameters $\beta_{j,m}$. The generation of the first and second derivation allows for computing the maximum of this function. As the first partial derivation of the logarithmized likelihood function is not linear, the utility parameters cannot be calculated in an unambiguous manner. Therefore an iterative algorithm, such as the Newton-Raphson algorithm has to be utilized. This algorithm maximizes the logarithmized likelihood function, beginning with a starting value. As the maximization can stop on a local maximum, which is not the real, global maximum of the data structure, it is suggested that the estimation be implement with an ample number of different, randomly chosen starting values (Train, 2009).

2.2.3 Assessing the goodness of the estimated utility parameters

Assessing the goodness of estimated utility parameters is conducted on three criteria: face validity of the estimated utility parameters, goodness of fit, and prognostic validity. Face validity, or plausibility, asks for compatibility of estimated utility parameters with a-priori assumptions regarding the value of the utility parameters. Goodness of fit assesses the portion of observed data that can be reproduced by the utility model. Maximizing the likelihood function means fitting the data to the model (the likelihood of the data, given the model): A high fit of the data to the model means a high goodness of fit, and thus high internal validity. Prognostic validity is assessed with the help of holdout samples (choice sets not used for utility estimation). The estimated utility parameters should forecast the choices in the holdout sample as well as possible.

Face validity can be assessed based on the estimated direction of impacts on the total utility. This direction can be observed directly by the sign of the estimated parameter. A positive sign leads to an increase of the total utility if this particular attribute level is available, and therefore to a higher choice probability. An interpretation of the intensity of a utility parameter can be conducted with a significance test of the estimated parameters, comparable to a *t*-test. Therefore, the matrix of the second derivative of the likelihood function is considered. This constitutes a variance-covariance matrix, which is labeled Hessian matrix, with the following characteristics:

(11) $$\Gamma(\hat{\beta}) = \left[-\frac{\partial^2 L\left(\hat{\beta}\right)}{\partial^2 \hat{\beta}} \right]^{-1}$$

Γ: Variance-covariance matrix

∂: Partial derivative

$\hat{\beta}$: Estimated parameters

The square root of the diagonal elements of this matrix results in the standard error of the parameter estimates. The proportion of the mean and the standard error of an estimated utility parameter results in the empirical *t*-value.

Evaluation of the goodness of fit is based on the value of the maximized likelihood function. The likelihood-ratio (LR) test compares the estimated model with a null-model *L(0)*, a model that assumes all parameters to be zero.

(12) $$LR = \left|-2\ln L(0)\right| - \left|-2\ln L(\hat{\beta})\right|$$

By multiplying the logarithmized likelihoods with "-2," the value of the likelihood-ratio test is asymptotically chi-square distributed with $|K|$ degrees of freedom, and thus allows for statistical inference.

Prognostic validity of the estimated utility function can be assessed on the basis of holdout choice sets. A measure reflecting prognostic validity, for example, is the average forecasted choice probability for a chosen option in the holdout choice sets. An error-based approach resembles the difference between estimated and observed choices in the holdout sample. Here, each holdout choice set is considered in respect of estimated utility (based on the empirically observed choices), and the observed choices. It is implied that respondents choose the option that holds the maximum utility.

Owing to the low information content of the nominal dependent variable (choice vs. no choice), parameters are estimated on an aggregated level. This means that individual preference structures are not considered in the standard MNL model. The inherent implication of a homogeneous preference structure is not problematic when considering monotonic rising attributes, in which "more" means "more utility" in most cases. In the case of nominal attributes, the assumption of a homogenous preference structure can result in biased parameter estimates, when respondents actually have heterogeneous preferences (Krieger, Green, & Umesh, 1998). Therefore, possible heterogeneity has to be considered when conducting discrete choice experiments. In the following subsection, the sources of heterogeneity, and possible solutions for parameter biases due to heterogeneity, are discussed.

2.2.4 Heterogeneity in preference elicitation

Heterogeneity in the analysis of preference basically means that respondents are different. On the basis of the total utility function (13), possible sources of differences can be illustrated.

(13) $$u_{h,i} = \Psi_h \left[v_{h,i,j,m} \left(x_{h,i,j,m}, \beta_{h,j,m}, \beta_{h,0} \right) \right] \forall h \in H, i \in I$$

$u_{h,i}$: Total utility of the i-th option for the h-th respondent

Ψ_h: Link function that combines the utilities of $|J|$ attributes and their attribute levels $|M_j|$ for the h-th respondent

$v_{h,i,l,m}$: Part of the total utility of the i-th option with j-th attribute and m-th attribute level for the h-th respondent

$x_{h,i,j,m}$: Value of the m-th attribute level regarding the j-th attribute at the i-th option for the h-th respondent

$\beta_{h,j,m}$: Utility parameter of the m-th attribute level of the j-th attribute regarding the h-th respondent

$\beta_{h,0}$: Parameter for the constant of the utility function for the h-th respondent

Concerning the measurement of preference, respondents can interpret the scale for option evaluation differently, which means the constant $\beta_{h,0}$ will be different across respondents. This is especially important for using rating scales to obtain the preference (DeSarbo, Lehmann, & Hollman, 2004). The solution of this heterogeneity problem would be the standardization (Fisher's-Z) of individual observations. As discrete choice experiments use choices as preference measures, the measurement scale as a source of heterogeneity plays a subordinated role (yet, see Swait & Louviere, 1993, for an opposing view).

Further sources of heterogeneity related to the measurement of preference (in contrast to the analysis of preference) are the perceived attributes $x_{h,i,j,m}$, and the link function of attribute utilities, Ψ_h (ideal-point, vector, or part-worth model). Both sources of heterogeneity can be diminished by a rigorous pre-test of the relevance of attributes, and the use of heuristics regarding the surveyed attributes. Therefore, these sources based on the measurement of preference can be considered a given in the analysis of preference. Here, the heterogeneity of preference, reflected by differences in the parameter for the attribute levels $\beta_{h,j,m}$, plays the major and more relevant role. Preference heterogeneity is given when respondents evaluate the presented attribute levels differently, based on their needs (Ben-Akiva et al., 1997, p. 274). Therefore, preference heterogeneity is of the utmost importance for deducing the marketing implications. Differences between respondents make it possible to approach potential customers with a differentiated product / service / advertisement. The challenge will be the appropriate modeling of the preference heterogeneity. The higher the difference between respondents, the less effective the aggregated modeling approach (Rossi & Allenby, 2003). In the following subsection, two approaches to account for heterogeneity in preference analysis are introduced, the mixed logit and finite mixture logit model, as these approaches are considered particularly useful for the objectives of this work.

2.2.4.1 Mixed logit models

Heterogeneity can be modeled on the aggregated, segmented, and individual level. Individual level models are not considered necessary for the purposes of this work and are therefore not addressed. The interested reader can learn more about individual level models in Kenneth Train's outstanding book "Discrete Choice Methods with Simulation" (2009).

Aggregated choice models assume that all respondents can be described by the same utility parameters. There is no possibility of differentiating utility parameters among respondents. A straightforward approach to include heterogeneity on aggregated level is to include additional respondent-related information. The deterministic utility of an option is modeled in the following manner:

(14) $$v_{h,i} = \beta \cdot x_i + \phi \cdot w_h \qquad \forall h \in H, i \in I$$

β: Vector of utility parameters for all respondents

x_i: Vector of attribute levels for the *i*-th option

ϕ: Vector of parameters for respondent related information

w_h: Vector of respondent related information

This approach assumes a systematic relationship between the respondent-related information and the heterogeneity in the preferences (Baltas & Doyle, 2001). Respondent-related information can be socio-demographic attributes, such as age, gender, income, etc. For example, Haaijer, Kamakura, and Wedel (2000) show how the inclusion of individual response time can account for heterogeneity. Overall, this approach constitutes a systematic adjustment of the nevertheless assumedly homogenous utility structure.

Random or mixed logit models assume that utility parameters of respondents follow a specified distribution (Revelt & Train, 1998). An advantage of mixed logit models is the obviation of the IIA property that is especially implausible in repeated choice experiments, in which choices are likely to influence subsequent choices, so that error terms are probably correlated (Train, 2009, Chapter 6). The specification of a distribution for the utility parameters (random effects) of the respondents, allows for the variation of these in the specified distribution across respondents. The assumption of a continuous monotonic distribution allows for the estimation of the mean and standard deviation of the distribution.

(15) $$\beta_h \sim g(\beta_h \mid \mu, \Gamma) \qquad \forall h \in H$$

β_h: Vector of the utility parameters for the *h*-respondent *g(•):* Density function of the random effects

μ: Vector of the mean of the distribution

Γ: Variance-covariance matrix

The function of the random effects is often assumed to follow a normal distribution. On the one hand, this distribution is assumed to adequately reflect the preferences of respondents. On the other hand, normal distribution facilitates the estimation of parameters due to its mathematical characteristics (Rossi & Allenby, 2003).

For the estimation of the likelihood function, it is assumed that respondents are independent from each other, so that a multiplicative linkage of the individual likelihood functions is allowed:

(16) $$L(u \mid \beta, \mu, \Gamma) = \prod_{h=1}^{H} L(u_h \mid \beta_h) g(\beta_h \mid \mu, \Gamma)$$

u_h: Vector for the total utility of the options for the *h*-respondent

The likelihood value for the estimated model is the result of the individual likelihood values regarding the distribution of the utility parameters. The estimation of the random effects parameters (mean and standard deviation) is conducted as follows:

(17) $$L(\mu, \sigma^2) = L(u \mid \mu, \sigma^2) = \prod_{h=1}^{H} L(u_h \mid \beta_h) g(\beta_h \mid \mu, \sigma^2) d\beta_h$$

Owing to the integration of the utility parameters of each respondent ($d\beta_h$), their identification is not feasible anymore. Thus, although heterogeneity is accounted for in random effects models by the parameters of the random effects distributions, utility is reported on an aggregated level. Simulation of the probability for a sequence of choices proceeds as follows:

1. Draw the utility of an option for the initial period, and calculate the logit formula for this period.
2. Draw the utility of an option for the second period, calculate the attribute level parameter (β_2), which is also based on the derived utility in the initial period, and then calculate the logit formula based on this β_2.
3. Continue for all choice sets.
4. Take the product of the logits for every choice set.
5. Repeat steps 1–4 for numerous sequences of draws (> 1000).

6. Average the results.

The burden placed on simulation is greater than is the case with coefficients, which are constant over time for each person; they require *x* times as many draws, in which *x* is the number of choice sets (Train, 2009, p. 147). The mixed logit approach to comply with heterogeneity, explained above, will be applied in the exploration of visual attention during preference decision-making.

2.2.4.2 Finite mixture models

Another segment-related approach to model heterogeneity is the finite mixture model. Here, the preference expressions are used as information to optimize the model fit with a given number of segments. Results are segment-specific utility parameters, with the assumption of a finite number of segments that are homogenous for their latent utility vectors. This implies that individual regression equations have to be aggregated to a segment-specific regression equation.

Finite mixture models assume one density function for all individual choices, whereas the choices resemble the basis for segmenting. Furthermore, it is presumed that the individual density function can be described by a finite number of conditioned density functions. Density functions are conditioned on the premise that the *h*-th consumer belongs to the segment *s*.

(18) $$g_h(u_h) = \sum_{s \in S} \eta_s, g_{h,s}(u_h \mid X, \beta_s \mid \Gamma_s)$$

g(•): Density function for the *h*-th consumer

u_h: Vector for the total utility of the options for the *h*-th respondent

$g_{h,s}$*(•)*: Density function for the *h*-th consumer by the condition that the consumer belongs to segment *s*

X: Design matrix

β_s : Vector of utility parameters for segment *s*

Γ_s : Variance-covariance matrix for segment *s*

The objective of the finite mixture model is the estimation of segment-specific utility parameters. The utility of attribute levels determines the total utility of an option, thus:

(19) $$u_{s,i} = \sum_{j \in J} \sum_{m \in M} \beta_{s,j,m} \cdot x_{i,j,m}$$

$u_{s,i}$: Total utility of option *i* in segment *s*

$\beta_{s,j,m}$: Utility parameter of the *m*-th attribute level of the *j*-th attribute for segment *s*

$x_{i,j,m}$: Value of the *m*-th attribute level of the *j*-th attribute regarding option *i*

The segment-specific total utility represents the mean of all option judgments in a respective segment:

(20) $u_{s,i} = \mu_{s,i}$

$\mu_{s,i}$: Mean of all judgments for option *i* in segment *s*

Hence:

(21) $$\mu_{s,i} = \sum_{j \in J} \sum_{m \in M} \beta_{s,j,m} \cdot x_{i,j,m}$$

The sum of segment-specific utilities of particular attribute levels represents the mean of option judgments in a segment. In this way, finite mixture models aggregate individual regression equations. It is important to note that if the assumption of homogenous segments is violated, the segment-specific mean no longer adequately represents the individual utilities.

As a first step, the maximization of the likelihood function with the additional parameter for the segments requires the specification of the number of segments. Subsequently, the expected value of the likelihood function is calculated, depending on the given preference expressions, a preliminary assessment of the segment size, and tentative segment-specific utility parameters. The expected values are then replaced by a-posteriori values of a Bayesian analysis and maximized. This process is iterated until convergence is reached (see Wedel & Kamakura, 2000, p. 120-124, for details). The finite mixture approach to comply with heterogeneity, explained above, will be applied in the exploration of affect and arousal during preference decision-making.

2.2.5 Indication of cognitive and affective processes in utility elicitation

The mathematical models of choice assume that human beings decide utility maximizing, which is not always the case (e.g., Tversky & Kahneman, 1981). Although the structural mathematical approach to the modeling of decision-making already shows some parallels to human cognitive functioning (Einhorn et al., 1979), the explicit incorporation of cognitive process indicators in modeling decisions could yield further important benefits. Especially the necessity to formulate and test hypotheses when incorporating cognitive process indicators could enable important progress in research (Johnson et al., 2008).

An interesting differentiation made by Kahneman, Wakker, and Sarin (1997) further supports the necessity of examining cognitive processes in decision-making. Kahneman et al. (1997) differentiate between decision utility and experienced utility. Experienced utility originates with Bentham (1789) and refers to the pleasure and pain associated to decision-making. Decision utility is inferred from observed choices by a more or less complex regression analysis and is in turn used to explain them (it is a circular concept). Only the synthesized observation of decision and experienced utility, represented by cognitive and affective processes, can break the circularity of the utility concept. Furthermore, this differentiated approach to the utility concept holds the chance to bridge the gap between the economic and behavioral perspectives. This synthesis would presumably result in a more realistic perspective on the utility concept, and therefore in more realistic predictions of choice behavior.

A promising approach to gain a deeper understanding of consumer decision-making, especially its fallacies (preference construction), is the consideration of mental processes with psychophysiological indicators. A variety of measurement techniques are used in consumer research to measure reactions to stimuli. These measures include behavioral measures (i.e. actual decisions), verbal measures (i.e. self-reported attitudes), and psychophysiological measures, (e.g. eye movement). However, researchers have been skeptical about verbal measures because of the restrictions they have for delivering effective measures of internal reaction to external stimuli (see Wang & Minor, 2008, p. 198).

There are several reasons for the plausible skepticism regarding verbal measures in consumer research. First of all, thoughts are complex, and thus cognitive processes of consumers confronted with typical consumers' tasks (deciding, buying) cannot be adequately measured by self-reported indicators (Wiles & Cornwell, 1991). Reliability and validity of self-report measures are further degraded as self-reports seduce respondents to give lip-service responses, such as socially desirable or thoughtless feedback (Nighswonger & Martin, 1981). Verbal measures of responses to stimuli are probably unreliable, as the process occurring between cognitive process and behavioral consequence cannot be reflected (Wiles & Cornwell, 1991). This is especially interesting, as consumers might have a "feeling of knowing," even though they cannot clearly retrace a memory (Zaltman, 2003). Zaltman (2003) found that in most cases, consumers cannot properly explain, by means of verbal measures, the reason for buying a specific product.

The use of psychophysiological measures in consumer research became a reality in the 1980s. Psychophysiological measures can "provide a very basic, unbiased, and sensitive measure of an individual's reaction to a stimulus [as] autonomic reactions are not under voluntary control [and] it is not possible for individuals to mask their 'true' reactions to a product" (Stewart & Furse, 1982, p. 2). Thus, psychophysiology allows for a precise, comprehensive, and unbiased measurement of the psychological process during consumer behavior and is not limited to outcomes (e.g., choices). It can reflect a broader and deeper intellectual understanding of consumers' cognitive and affective mechanisms.

Psychophysiology is an interdisciplinary field that conglomerates physiology, biology, and psychology (Kroeber-Riel, 1979). It is defined as “the study of relations between psychological manipulations and resulting physiological responses, measured in the living organism, to promote understanding of the relation between mental and bodily processes” (Andreassi, 2009, p. 1). Based on a vast amount of research (e.g., Cacioppo, Tassinary, & Berntson, 2000), consumer research can already use and benefit from physiological indicators for covert psychological processes (Wang & Minor, 2008).

The following chapters present the theoretical basis for the hypotheses, which concern the incorporation of cognitive and affective process indicators in discrete choice models. As every cognitive process is generally dependent on memory, the role of memory in decision-making will get a closer look. Building on the aspects of human memory, a theoretical background to attentional and affective processes in consumer decision-making, as well as relevant hypotheses, will be offered.

2.3 Memory processes in decision-making – sources of preference construction

Memory is the most relevant attribute of the human brain. Without memory, every moment would appear like an awakening from a life-long sleep: Every person would be a stranger, every action would be a challenge, and every word would be experienced as if for the first time. Memories define what persons do and who they are. Apart from some hardwired preferences by evolution (sweet is preferred over bitter, etc.), memories also define what people like and how they choose (L. L. Birch, 1999).

Although it seems quite plausible that memory processes are crucial for decision-making, their role in consumer decision research has largely been ignored (Weber & Johnson, 2000). Economic and behavioral decision research neglected memory processes and concentrated on preference and choice as “as-if” mathematical representations. A little more than a decade ago, a number of researchers started to take interest in the impact of implicit memory processes on decision-making (Arkes, 2001).

Even though differentiations of memory like implicit / explicit, episodic / semantic, and the general interplay of memory processes (dual-process / fuzzy-trace) are important issues and have serious consequences for decision-making, the following subsection concentrates on a “micro”-level of memory processes. A focus on cognitive and functional findings, rather than computational models of human memory, is more constructive for the scope of this work.

2.3.1 Functional relationships between memory and preference

Formal models of preference map stimuli to their internal experience, e.g., von Neumann-Morgenstern utilities (1953). Combinations of different levels of attributes generate hedonic value or utility, which is described by mathematical functions. These mathematical formalizations make implicit assumptions about the psychology of choice, which are easily falsified and not in line with research on human memory (Weber & Johnson, 2000). Choices can be conceptualized as the output of the human memory system, since there is little reason for knowledge related to preferences not to possess the properties of other types of knowledge. Conceptualizing decision-making as a product of memory processes might shed light on possible deviations from the functional choice modeling approach (Weber & Johnson, 2009).

The first assumption of mathematical models of choice is procedural invariance: Deduced utility is usually assumed to remain constant over time and across measurements procedures. Findings in cognitive psychology suggest that preference might differ as a function of differences in short term accessibility, e.g. as the result of priming (Krajewski, Sauerland, & Muessigmann, 2011).

The second assumption is continuity: Mathematical models of utility use continuous functions to describe the interplay between attribute levels and utility; no discontinuities are assumed. Memory episodes are discrete in nature, as memory processes are excitatory or inhibitory (J. R. Anderson, 2005). Thus, it is suggested that preferences might be discontinuous.

The third assumption is precision: As continuous lines represent utility in mathematical models of choice, the utility of an attribute level is infinitely precise. As memory is presumably reactive, i.e., assessing memory changes it (Chapman & Johnson, 1999), this assumption does not fit with the notion of precise utility representations.

In the following subsection, the functional characteristics of memory in decision-making are discussed in order to develop a basic understanding of indicative psychophysiological processes in decision-making, such as visual attention and affective processes.

2.3.2 Memory structure

In order to predict how memory processes affect accessibility and thus choice behavior, a profound understanding of how memory is organized is necessary. Most concepts stored in memory (e.g., the yogurt you plan to eat for breakfast) have rich, structured and hierarchical representations. Others, like utility (e.g., money, or time) might have a very different, probably impoverished, and less structured representation.

Memory theorists argue that the most important issue for memory retrieval is the number of connections between a concept node and associated nodes (node means memory content). The number of connections determines the likelihood of retrieval of subordinated nodes. This phenomenon is often called the fan effect (J.R. Anderson & Reder, 1999). Given a memory cue (e.g., a product as choice option), the likelihood that associated information is retrieved (product attributes) is a decreasing function of the number of connected nodes. Thus, product attributes with many associated nodes are less likely to be recalled than product attributes with fewer associates. The hierarchical organization of memory is a means to counteract the fan effect. Organization of information in hierarchies of information and sub-information ensures that a manageable number of interconnections can be accessed (J. R. Anderson, 2005).

Assuming a balanced organization of knowledge in memory, the strength of the connection between memory cue and associated information in the mind impacts the likelihood of retrieval (M. C. Anderson & Neely, 1996): The stronger the connection, the higher the likelihood of retrieval. The following subsection examines the accessibility of memorized items.

2.3.3 Memory accessibility

Memory content that is to be accessed is to be retrieved and thus likely to influence revealed preference. The presentation of a stimulus can lead to an increase in the accessibility of the same stimulus and associated concepts (Bargh, Chen, & Burrows, 1996). This phenomenon, in which the activation of a memory node affects later accessibility in a positive manner, is called priming.

A supermarket experiment by North, Hargreaves, and McKendrick (1999) linked priming and revealed preference. They played music with either stereotypical French or German characteristics in a wine shop. More of the French wines were sold on the days French music was played, while more of the German wines were sold when German music was played. The variation of music accounted for almost a quarter of the variance in wine sales. Further supporting this externally valid priming-preference link is the insight that respondents were unaware of the impact of music and even denied the priming effect after a de-briefing.

Mandel and Johnson (2002) examined the effects of priming on consumer choice in an impressive experiment. They selectively primed specific product attributes by manipulating the background (the wallpaper) of an online-shop website. Pre-tests showed that backgrounds of blue sky with clouds primed the feature comfort, leaving the accessibility of other features unchanged. Respondents who were confronted with several couch options and had seen the blue sky background were more likely to choose a more comfortable but more expensive couch than a control group. Participants who saw a green background with embedded pennies were more likely to choose a less comfortable but less expensive couch compared to a control group.

In addition to the examination of priming on consumer choice, Mandel and Johnson (2002) took a closer look at the visual attention paid to the primed attributes. Research by Biehal and Chakravarti (1986), who have shown that brand accessibility can influence the amount of information sought about the brand as well as brand choice, suggests the impact of primes on visual attention on brand level (see also Ratneshwar, Warlop, Mick, & Seeger, 1997, who showed that subjects have a higher recall and recognition of a product benefit that is made salient). Results of Mandel's and Johnson's (2002) wallpaper experiments showed that priming does influence visual attention. Subjects primed on money (green background with pennies embedded) looked up more price information than subjects primed on comfort (blue sky with clouds in the background). Interestingly, this effect is particularly true for novices in the field of couch shopping. Experts did not look up more prime-consistent information. It is even more interesting to note this does not affect the impact of priming on expert choice, which is as biased as the novice choice by the primes.

These findings point to the power of priming (even experts can be biased), and the close interrelationship of priming, accessibility, and visual attention. As visual attention seems to be a reliable indicator of memory processes during decision-making, this work utilizes visual attention in order to explore its indicative power in consumers' stated preferences.

2.3.4 Affective priming

Human memory constitutes an experiential system that consists not only of knowledge (episodic / semantic) but also of affect, which is connected to that knowledge. For example, if we see a house, associated knowledge about houses comes to our mind (houses have doors and windows, etc.). Zajonc (1980) argued that all perceptions contain some affect: "We do not just see "a house": We see a handsome house, an ugly house, or a pretentious house" (p. 154). Affective reactions to stimuli are often first reactions due to automaticity (Zajonc & Markus, 1982). Thus, affective reactions play a major role in guiding information processing and judgment.

It is assumed that human memory and the experience of affect are tightly intertwined (Epstein, 1994). Although pondering pros and cons in some decision context is certainly important, reliance on affect is a quicker, easier, and more efficient approach to guide behavior in a complex and uncertain world. Epstein's (1994) perspective is as follows:

"The experiential system is assumed to be intimately associated with the experience of affect, […] which refer[s] to subtle feelings of which people are often unaware. When a person responds to an affectively significant event […] the experiential system automatically searches its memory banks for related events, including their affective accompaniments […]. If the activated feelings are pleasant, they motivate actions and thoughts anticipated to reproduce the feelings. If the feelings are unpleasant, they motivate actions and thoughts anticipated to avoid the feelings." (p. 716)

Just like the cognitive computation of utility, affect might serve as an important cue for many judgments. The use of a readily available affective impression can also be far easier, quicker and more efficient than analyzing utility probabilities of different options. This is recommended especially when decisions are complex or mental resources are limited.

An impressive series of experiments by Zajonc demonstrated evidence for the fundamental character and importance of affect (Zajonc, 2001). His central finding is that the repeated presentation of objects to an individual can create a positive attitude or a preference for these objects - a phenomenon often called "mere exposure." A typical study setup is the presentation of stimuli such as nonsense phrases, faces, or Chinese ideographs to an individual with varying frequencies. The individual judges these stimuli on liking in a later session. The frequency of exposures was found to reliably enhance affect toward visual, auditory, gustatory, abstract and social stimuli (see Bornstein, 1989 for a meta-analysis over 200 experiments).

Enhanced affect is not only the result of repeated exposure but can also influence the outcome of judgments. Winkielman, Zajonc, and Schwarz (1997) demonstrated the speed and persistency with which affect can influence judgments. Participants were primed through exposure to a smiling face, a frowning face, or a neutral polygon for 1/250 of a second. This period is so short that no recognition or recall of the stimulus is possible. Instantly following this exposure, an ideograph was presented for two seconds. Subsequently the participant rated the ideograph in respect of liking. Results showed that liking ratings were significantly higher for ideographs preceded by smiling faces. Another priming in a later session with a frowning face or neutral polygon showed no effect, presumably due to the persistency of the first priming.

Various further studies have shown that affect is a strong conditioner of preference, independently of whether the affect is consciously perceived or not (LaFrance & Hecht, 1995; Sherman & Kim, 2002). Owing to the automaticity, speed, and likely unconscious experience of affect in consumer choice, this work strives to explore the effect of affect with the help of psychophysiological indicators of affect (skin conductance / facial muscle activity).

2.3.5 Reactivity of memory

Comparable to Heisenberg's uncertainty principle (Heisenberg, 1991 [1968]), mere data collection can impact the behavior of an observed object, which also holds true for memory. The mere act of asking a question can influence the subtleties of memory accessibility, which go beyond the effects of priming. Chapman and Johnson (1999) asked subjects if their sales price for a bet was higher or lower than the last four digits of their social security number. Although normatively irrelevant, this relative evaluation affected their selling prices for the gamble significantly. Subjects denied this effect when asked in a de-briefing (replicated by Ariely, Loewenstein, & Prelec, 2003). This phenomenon is often labeled the anchoring effect and can be attributed to a short-term raise in the accessibility of memory content. Based on, e.g., the selective accessibility model (Strack & Mussweiler, 1997), and Chapman's and Johnson's (1999) anchoring as activation model, an anchor leads to higher accessibility of anchor consistent information. Thus, this information is more likely to be included in subsequent judgment. Trivially, the anchor must be used in a preliminary judgment for anchoring effects to occur. It could be possible for options used in sequential stated preference surveys, such as discrete choice experiments, to act as an anchor and thus bias subsequent judgments. Accessibility may not be sufficient to explain every anchoring effect (Epley & Gilovich, 2001), yet accessibility-related anchoring effects are also strong, robust, and persistent in the presence of incentives, experience, and feedback (Ariely et al., 2003).

Morwitz, Johnson, and Schmittlein (1993) hinted at the permanence of changes in accessibility. In their analysis of household panel data in respect to the purchase intention of computers and automobiles, the mere measure of purchase intention changed the actual purchases. As a result of answering a question about a purchase intention, actual purchases increased by about one-third several months later in comparison with those by households that were not asked for their purchase intention.

In summarizing the findings regarding the accessibility of memory, it seems that just as false memories can be induced (e.g., being lost as a child in a shopping mall, Loftus & Pickrell, 1995), one can also induce false preference, for example just by asking people about their behavioral intentions (Morwitz, 1997). As explicit memories of such measurements typically do not exist, conscious mental processes cannot explain such effects. The focus on the unconscious fast memory process does not even have to be induced by the context (in the form of an experimenter asking questions, for example) but can also be self-induced by memory interrogation.

2.3.6 Memory interrogation – order of queries

The preference as memory (PAM; developed by Weber & Johnson, 2000) framework assumes that decisions are taken by retrieving decision-relevant knowledge from memory in order to determine the best action. A major assumption is that consumers generate utility predictions (preference) by a series of component queries about the attributes of choice alternatives. Consumers ask themselves what is good (or bad) about an option in a serial fashion.

When asked to pick a preferred music CD (compact disc) from a set of three, people consult their memory about previous experiences with the same or similar CDs. These queries are presumably grouped by valence, as this helps to generate and integrate knowledge (a hierarchy based on valence). For example, memory is first queried about the good attributes of the CD, and only after no positive attributes are generated, a query about the bad attributes could follow. Most tasks suggest a natural approach to the order of queries. Being asked to buy a CD out of three naturally triggers queries about positive features, whereas being asked to reject a CD naturally triggers queries about negative attributes (Shafir, Simonson, & Tversky, 1993). Comparably, homeowners asked to provide a selling price for their home first focus on positive attributes, before considering the downsides. A potential buyer might pose these queries in an opposite order (Birnbaum & Stegner, 1979).

It is not assumed that such memory interrogations are explicit or conscious, even though they can be. It is more likely that memory interrogations occur without conscious effort as a natural and automatic part of preference expression. The order of queries can be of importance due to interference processes. Interference and inhibition work on the process of memory interrogation and thus affect answers provided by memory, and preference. The following subsection provides a closer look at the interfering and inhibitive processes in decision-making.

2.3.7 Interference and inhibition in memory processes

While priming increases accessibility, other tasks or events can affect accessibility negatively. A classic memory phenomenon of inhibition is depicted by the following example: Imagine you have just moved to another city and have not yet memorized your new address (street name, house number, zip code, etc.) completely. You want to have your correspondence delivered to your new address and are asked to give it to the delivery service. When you have almost remembered it, the post office employee reads out your old address, asking you if that is it. It is now almost impossible for you to recall your new address.

The common idea of all research on the interference effect is that recalled parts of memory temporarily suppress the recall of unrecalled response competitors in memory. Inhibition of response competitors is partially responsible for the phenomenon that unrecalled items cannot be recalled when asked for. The effects of competing material are some of the oldest and most developed memory phenomena. Anderson & Neely (1996) review the theories and results of inhibition effects, which are the result of prior recall of related and competing material. Interference has been shown to occur for both semantic and episodic memory, as well as for verbal and non-verbal materials, for example pictorial stimuli (M. C. Anderson & Neely, 1996). Current studies demonstrate that interference effects also work on implicit memory (Lustig & Hasher, 2001).

The functional advantage of memory processes, such as inhibition, but also priming, is the facilitation of action. Humans are not developed to contemplate and investigate but to act in ways that maximize survival (Payne et al., 1993). People are probably wired by evolution to take the best action / option quickly. Inhibitory and excitatory (priming) memory processes facilitate the rapid emergence of a decision response, which is associated with a positive utility maximizing outcome based on prior experience.

The goals of the decision task (e.g., pick the best option or reject the worst option) and choice contexts (e.g., options in a choice set) influence the focus of attention, which translates into a series of memory interrogations. In turn, these memory interrogations result in amplified activation of response consistent information (priming) and decreased activation of response inconsistent information (inhibition).

An early focus on a choice alternative will result in greater accessibility of features consistent with this option, and reduced accessibility of features inconsistent with this option. Russo, Meloy, and Wilks (2000), for example, find an early bias in the examination of choice options in favor of a primarily selected option. By contrast, Reisen, Hoffrage, and Mast (2008), and also Wedell and Senter (1997, p. 61), found that people often start decision-making with an elimination-by-aspects strategy, and thus an early focus on the negative, options they will eliminate. In both cases, memory interrogation leads to interference, meaning that early memory inquiries, either for liked or disliked options, inhibit possible responses to later inquiries.

Hoch (1984, 1985) analyzed interference in the prediction of future purchase intentions. Participants in these studies were asked to provide reasons why they would pick or reject a consumer product in the future. The order of the two tasks (reasons for picking / reasons for rejecting) was counterbalanced in a between-subjects design. Consistent with the assumption that the first task would interfere with the second task, independently of the task goal (pick vs. reject), Hoch found that the first task generated more reasons than the second task. Furthermore, participants were more liable to foresee that they would pick an item when they generated reasons for picking it first, even though everyone answered both types of questions (pick and reject). Hoch (1985) separated the reason provision task from the purchase intention task in time to confirm that the effect is based on memory interference. No evidence of interference was found in this second study. Instead, a recency effect was observed, in which the outcome of the second task attained more weight in predicting purchase intention independent of task goal.

The order of memory interrogations and according inhibitive processes might play a major role in the analysis of consumer choices with the goal to derive utilities. Therefore, this assumption is to be explored with visual attention measures as an information processing indicator in discrete choice experiments.

The presented research pertaining to the impact of memory accessibility, affective priming, and memory interrogation suggests that consumer choice processes could somehow always be biased, and therefore constructed. This work strives to explore memory-based factors that influence this bias to a greater or lesser extent during consumer decision-making in discrete choice experiments (DCEs). As DCEs have the clear objective to analyze and predict utilities (preference) the link between basic memory processes and utility should help to deepen the understanding of possibly constructive preference expressions. In this work, the means to investigate basic cognitive and affective processes in consumer decision is the additional measurement of psychophysiological processes. Consequently, the next chapters provide a sound theoretical and empirical investigation of the role of visual attention, affective valence, and arousal in consumer choice.

3 Visual attention in consumer decision-making

The term "attention" is widely used, but unfortunately it is poorly defined despite a vast amount of research in the past decades (see Carrasco, 2011 for a review). Attention is best described by explaining what it does: It allows us to selectively process the enormous amount of information with which everyone is confronted. Attention prioritizes some features of information while ignoring others by focusing on certain aspects. Owing to severe limits of human information processing, ignoring irrelevant information allows humans to attend and to interpret the important aspects of what we see. Pashler (1989) reviewed several more or less vague definitions of attention and found three central aspects: selectivity, capacity limitation, and effort. These aspects account for the phenomena that we can process some incoming stimuli better than others, show an obvious limit on the ability to carry out simultaneous processing, and have to make a considerable effort towards the sustained processing of information.

Petersen and Posner (2012) suggest a finer-grained perspective on attentional processes, which is related to different tasks of attention: alerting, orienting, and executive control. Alerting is defined as maintaining a state of high sensitivity to incoming stimuli (in the sense of vigilance), orienting is the selection of information from sensory input, and executive control involves the mechanisms for resolving conflict among possible responses. All three tasks of attention proposed by Posner and Petersen (2012) have a direct link to decision-making, as alertness determines the amount of input during decision-making, orientation the selection of decision-relevant information, and executive control the actual selection of an option (choice).

Another differentiation of visual attention is concerned with the unit of attentional selection. Three main types of visual attention are differentiated (Carrasco, 2011): spatial attention (location of attention), feature-based attention (deployed to color, contrast, orientation, etc., of objects), and object-based attention (attention is influenced, guided by objects). Especially the latter two perspectives play a major role in decision-making, as this differentiation opens the question of how attention is influenced during decision-making: by features, or by objects? This question is closely related to the issue of whether attention is guided by memory (object recognition), or by context (feature impact). The answer to this question is crucial for the psychological meaning of visual attention in the process of decision-making. In the former case, visual attention represents information processing; in the latter, context-dependent automatic attraction.

Humans typically pay attention to stimuli one after the other, i.e. serially (e.g., Treisman & Gelade, 1980). But which stimulus or option in a decision context is focused first depends on two types of attentional mechanisms (Treisman & Gelade, 1980). Bottom-up mechanisms are suggested to operate on raw sensory input, rapidly and automatically shifting attention to salient visual features. An example for bottom-up attention is the automatic attentional capture of a red apple lying on a green lawn. Top-down mechanisms implement longer-term cognitive strategies, biasing attention toward goal-consistent objects, for example a colored spot on the lawn if you are hungry.

Psychologists examine top-down and bottom-up effects typically in abstract singleton experiments (e.g., Egeth & Yantis, 1997). In a set of trials, participants are asked to search and identify a uniquely colored singleton. The search display is immediately preceded by a cue display, which also contains a colored singleton. Even though participants are instructed to ignore the preceding cue, because it is irrelevant, the cue attracts attention, as assumed in a fast bottom-up fashion. The colored singleton cue also affects how quickly participants respond to a target. When the cue appears in the same location as the target, reaction times are faster. When the cue appears in a different location, response times are longer. Attention is temporarily drawn away from the target location and makes responses slower. This bottom-up effect is modulated by participants' top-down attentional state. Colored cues only affect response times when the participants search for a colored target. A red singleton will capture attention (bottom-up) if an observer is looking for the color red but not for the color green (Folk & Remington, 1998). Thus, bottom-up attention alerts humans to salient items, but top-down attention modulates (weakens) bottom-up signals when looking for specific options. Considering the time course of visual attention, Theeuwes, Atchley, and Kramer (2000) found bottom-up effects to dominate visual search up to 150 ms, which is an extremely short time span. After those 150 ms, top-down effects gain control and thus modulate visual search in a goal-consistent fashion.

3.1 Theory of visual attention

A model of visual attention allowing for the interaction of top-down and bottom-up effects is the "theory of visual attention" (TVA, Bundesen, 1990). This modern and increasingly accepted approach to visual attention accounts for many psychological phenomena of visual attention, and it is mathematically formulated (thus verifiable) and neuronally plausible (Bundesen, Habekost, & Kyllingsbæk, 2005). The core of the TVA is represented by two equations that jointly describe two mechanisms of attentional selection: filtering (selection of objects) and pigeonholing (categorization). In a first step, filtering, all perceived features are represented and weighted, followed by a second step, pigeonholing, in which the features are categorized in a first-come –first-served manner. If and only if the categorized features reach the visual short-term memory, the feature is ready to be processed. Bottom-up, as well as top-down processes are incorporated in both attentional mechanisms. The weighting w_x of objects in the receptive field, filtering, is formulated as follows:

$$w_x = \sum_{j \in R} \eta(x,j) \cdot \pi_j$$

R: Amount of visual categories (color, form, orientation, etc.)

$\eta(x,j)$: Sensory evidence for object *x* belonging to category *j*

π_j: Relevance of category *j* for observer (more important categories gain weight)

The sensory evidence accounts for bottom-up processes, whereas the relevance of a category accounts for goal-directed and memory controlled top-down effects. The race for the first categorization of object categories, pigeonholing, is formulated as follows:

$$v(x,i) = \eta(x,i) \cdot \beta_i \cdot \frac{w_x}{\sum_{z \in S} w_z}$$

v(x,i): Velocity of the categorization

$\eta(x,j)$: Sensory evidence for object *x* belonging to category *j*

β_i: Perceptive bias of categories based on the relevance of categories for the observer

$\frac{w_x}{\sum_{z \in S} w_z}$: Proportion of the weight of object *x* in relation to the weight of all objects

Again the sensory evidence based on the filtering process accounts for the bottom-up effect, whereas the relevance of categories represents the top-down effect in categorizing and probably recognizing objects. The general acknowledgment of very early top-down affects makes visual attention a valid indicator of memory-based information processing. This indication is important for research on consumer decision-making, as visual attention could be used to infer the relevance of options, when decision-makers observe choice options. In the following section, research on visual attention during decision-making is presented in order to clarify the meaning of information processing indicated by visual attention.

3.2 Visual attention in decision-making

Most theories of decision-making have been silent about the role of attention during decision-making, although assumptions exist more or less implicitly. Usually it is assumed that attention serves the decision-maker by passively acquiring information according to his or her needs. Recent developments in decision research have questioned the passive information-acquiring role of decision-making (see Orquin & Mueller-Loose, 2013 for a review). There are first steps to incorporate process measures, such as fixation or self-reported non-attendance in choice modeling (Hensher & Greene, 2010; Scarpa, Zanoli, Bruschi, & Naspetti, 2013). By relaxing the assumption of passive information acquisition, these models begin to acknowledge that attention itself has an impact on choice. This notion is captured by drift diffusion models; assuming that decisions are based on accumulated evidence, which is sampled during decision-making (e.g., Krajbich, Armel, & Rangel, 2011). The growing acknowledgment of the active role of attention calls for a closer look at the two constituting processes, bottom-up and top-down control, during decision-making.

The debate about bottom-up effects in decision-making has focused on the role of visual saliency. Saliency models assume that a visual scene is first encoded in parallel. Based on this receptive input, a topographic saliency map is computed that guides visual attention. Visual saliency consists of different aspects such as contrast, color, orientation of edges, and movement (Foulsham & Underwood, 2008; Itti & Koch, 2000). Although visual saliency is shown to affect encoding to visual short-term memory (Nordfang, Dyrholm, & Bundesen, 2013), its impact on encoding is generally smaller than that of top-down control (Orquin & Mueller-Loose, 2013). Therefore, some impact of bottom-up, low-level salient features will occur in decision-making. Decision-makers are more likely to attend to salient options, regardless of its importance for the decision. However, the effect of saliency on attention should also interact with goal-driven top-down processes. Decision-makers will also be more likely to attend to options that share goal related features.

Yarbus (1967) was the first to experimentally analyze top-down control of visual attention. He instructed participants to inspect a photograph with different goals in mind. It was shown that visual attention patterns differed according to the viewing task. Participants gazed at those parts of the photograph that were most relevant to their task. Task relevance has been identified as the primary driver of attention (e.g., Hayhoe, Shrivastava, Mruczek, & Pelz, 2003). With regard to decision-making, it is expected that decision-makers will attend to stimuli with higher task relevance and ignore stimuli with less or no task relevance. In the case of consumer decision-making, the expected utility is assumed to determine the task relevance of stimuli.

It was often observed that participants tend to gaze at information that has a higher utility or importance with regard to their decision. This utility effect (Orquin & Mueller-Loose, 2013) is a very robust finding regarding visual attention in decision-making. The most general finding, which is supported by a high number of studies, is that participants fixate more on the option they eventually choose (Glaholt & Reingold, 2009a; Schotter, Berry, McKenzie, & Rayner, 2010; Shimojo, Simion, Shimojo, & Scheier, 2003; Wedell & Senter, 1997). Furthermore, decision-makers are more likely to fixate on the chosen alternative first (Glaholt & Reingold, 2011; Schotter et al., 2010), and to spend their last visual visits oriented toward the chosen alternative (Krajbich et al., 2011). There are also several findings demonstrating that the likelihood of choice inspection increases until the decision is made (Fiedler & Glöckner, 2012; Glaholt & Reingold, 2009b; Simion & Shimojo, 2006). This phenomenon, also referred to as gaze cascade, was first described by Shimojo et al. (2003). They proposed that the gaze cascade effect consisted of two reinforcing processes (feedback loop): preferential looking (E. E. Birch, Shimojo, & Held, 1985), and mere exposure (Zajonc, 1968). Shimojo et al. (2003) also suggested that the allocation of the gaze to the eventually chosen option serves as a somatic marker and would be exclusive to preference decision-making. The notion of a gaze cascade as result of a feedback loop was later rejected (Schotter et al., 2010), as was the notion of preference exclusiveness (Glaholt & Reingold, 2009a). Nevertheless, a gaze bias to the later chosen option is a stable phenomenon in decision-making.

Another observation often reported is the u-shaped attention attribute-importance relationship (Meißner & Decker, 2010; Orquin & Mueller-Loose, 2013; Sütterlin, Brunner, & Opwis, 2008). The higher and the lower the importance of an attribute level, the more attention is devoted to it. This phenomenon is even observable during memory retrieval in decision-making. Participants gaze at empty locations where previously important attribute information was presented (Renkewitz & Jahn, 2012). All studies concerned with the utility effects of visual attention support the notion that visual attention and utility might be guided by a common underlying preference system. To date, however, it has been unclear how visual attention affects the analysis and prediction of consumer preference. Furthermore, stages of decision-making could change the meaning of visual attention in respect of utility. The role of visual attention in the analysis and the prediction of choice, as well as its eventually changing meaning in different stages of decision-making will be discussed in the following.

3.3 Visual attention predicts consumer choice

Pieters and Warlop (1999) were the first to focus on the differences between a conceptual analysis and a perceptual analysis of marketing stimuli [1]. Whereas the conceptual analysis focuses on stimuli that have already captured the consumer's attention and are already integrated in the pre-existing knowledge structure of the consumer, perceptual analysis tackles the process of integration. Before and during conceptual analysis, consumers engage in perceptual analyses (Greenwald & Leavitt, 1984). Consumers devote focal attention to features of the stimulus, such as color, size, and shape, categorize these in codes, such as pictorial and textual information, and eventually choose one option over the other. Marketing practitioners as well as academics commonly held the belief that attention and choice are closely related. That is why manufacturers draw on vibrant packages to make their product special, and retailers manage shelf space and displays to draw attention to products they prefer to sell (Allenby & Ginter, 1995). Pieters and Warlop (1999) were the first to establish the empirical proof for this attention-choice relationship. They acknowledge that theory-based predictions about the relationship between visual attention and choice are difficult, which is understandable because of the poor stock and the subsequent boost of research that followed this study. Sixty-four individuals participated in this eye-tracking study and had the task of choosing the most attractive of six shampoos they were presented with. Results show that the duration of visual attention as well as inter- and intra-option comparisons impact consumer choice. Pieters and Warlop (1999) conclude that "[consumer] choice can be predicted from observations of visual attention patterns only" (p. 14). Options that received more visual attention, more inter- and intra-option comparisons, indicating option-related information processing, had a higher likelihood of being chosen.

This pioneering work of Pieters and Warlop (1999) supports the reasonable assumption that visual attention is a window into a fine-grained utility concept stored in the memory of consumers. That is what choice models assume to analyze, but utility elicitation is not yet connected to the analysis of visual attention. Thus, this study utilizes visual attention to analyze the impact of visual attention on the utility of attribute levels, which constitute the option.

Following the work of Shimojo et al. (2003), it is assumed that visual attention serves as a somatic marker of preference. This assumption is shown to be confirmed in a series of choice situations but not, to date, in

[1] The article of Pieters and Warlop (1999) is the 2013 winner of the Jean-Benedict E. M. Steenkamp Award for long-term impact awarded by the European Marketing Academy and the International Journal of Research in Marketing.

a repeated choice paradigm that analyzes metric utility measures for attribute levels (discrete choice experiments). Therefore, the following hypothesis is postulated:

H1.1: The substitution of behavioral choice with the option that received more visual attention will improve internal and predictive validity of preference measurement compared with a purely behavioral choice model.

As this hypothesis and the research presented so far is undifferentiated with regard to the time course of visual attention, the temporal vicissitudes of visual attention in preference decision-making will get a closer look in the following section. The differentiated consideration of processual stages in decision-making could lead to significantly distinctive interpretations of psychological antecedents of visual attention effects.

3.4 Time course of visual attention in consumer choice

Most examinations of gaze bias consider the entire decision duration when making a choice (e.g., Pieters & Warlop, 1999). Examinations of gaze bias (implicitly) assume that positive or affirmative attributes are looked at longer, based on a “preferential looking” effect (Fantz, 1961; Shimojo et al., 2003). It is argued that this is not plausible in every stage of decision-making. For example, bottom-up features (shape, luminance, color) eventually draw attention during the observation of options, which makes visual attention useless as an indicator for preference. Irrelevant attributes first have to be identified, and looked at, before individuals can focus on the relevant attributes. Furthermore, decision-relevant attributes do not have to be positive (as gaze bias implies), but can also be negative, in an elimination-by-aspects manner (EBA, Billings & Marcus, 1983). These notions are supported by empirical results that show no linear relationship between the relative amount of visual attention on an attribute and the importance of that attribute (Harte & Koele, 1995, p. 10; Meißner & Decker, 2010).

Visual attention is based on the different underlying cognitive processes that relate to different stages of preference decision-making. Thus, different cognitive processes are in turn reflected by visual attention, which serves the goal of the cognitive process: either rejection or choice of a given option. A closer look at the gaze bias in specific stages of preference decision-making should help to understand which goal (approach / avoid) visual attention is serving at that time. Regarding choice construction, it is most interesting to identify stage(s) and processes responsible for the possible construction of choice. In order to reflect the underlying processes of gaze bias in the time course of preference decision-making, three stages are distinguished: orientation, evaluation, and verification (Russo & Leclerc, 1994; Wedell & Senter, 1997).

In the orientation stage, individuals gain a first impression of the presented alternatives. In this stage, bottom-up effects are likely to steer visual attention (van Zoest, Donk, & Theeuwes, 2004). In the first 150 ms, visual attention is completely controlled by bottom-up attention; after that time period, top-down control is likely to engage in selective attentional processes (Theeuwes et al., 2000). In line with that research, Milosavljevic, Koch, and Rangel (2011) found that consumers can identify two different food brands and make up their minds about which one they prefer in as short as 313 ms. That means, there can be top-down control very early in preference decision-making.

These findings lead to the assumption that memory-controlled top-down attention engages even in the first moments of observation. Reisen and Hoffrage (2008), and also Wedell and Senter (1997, p. 61), found that people often start with an elimination-by-aspects strategy, and then switch to a compensatory strategy to make a decision (in line with previous research, see Billings & Marcus, 1983). It is argued that gaze bias in the orientation stage reflects the goal of an initial elimination of unwanted attribute levels, in order to avoid an eventually wrong choice very early in the process of decision-making. In this case, visual attention indicates the opposite of a preferential gaze bias (i.e., the eliminated option) and no erroneous choice construction. Therefore, the substitution of behaviorally expressed choices with options that receive more visual attention should lead to a contrary content-related result, compared with the result based on behaviorally expressed choice.

H1.2: Substitution of behavioral choice with the option that was more attended to in the orientation phase will result in an opposite preference structure compared with a preference structure based on purely behavioral preference measurement.

In the evaluation stage, alternatives are compared with deliberation and effort to form a judgment (Russo & Leclerc, 1994). In this stage, different evaluation strategies are used (conjunctive, disjunctive, satisficing, etc.; see Harte & Koele, 1995). Independent of the strategy in use, the goal of the underlying cognitive process is to trade-off the given attribute levels. The trade-off between positive and negative attribute levels cannot proceed without regress on memory. When comparing two alternatives with regard to an attribute, say taste, we have to rely on the knowledge stored in memory (which taste is more favorable to us, strawberry or lemon?) in order to judge the alternatives on that attribute.

As bottom-up control of visual attention can be overpowered with top-down control in the evaluation stage, and memory of preferred attribute or meta-attribute is necessary for evaluation, it is assumed that in the evaluation stage, top-down control of visual attention is dominant. Nevertheless, it is assumed that more attention to an attribute in this stage does not have to indicate preference but rather represents importance (Reisen et al., 2008; van Raaij, 1977). Negative and positive attribute levels can gain equal amounts of attention at this stage, as both have to be compared in order to form a judgment. Therefore, more attention on an alternative should indicate that this alternative combines attributes that are important but not necessarily preferred. This is supported by empirical results from Shimojo et al., (2003), and Glaholt and Reingold, (2009b), who found no significant bias to the chosen option until 0.6 sec before choice (clearly after a possible evaluation) in two alternative forced-choice (2-AFC) tasks. The often-reported observation of a U-shaped attention attribute-importance relationship (Orquin & Mueller-Loose, 2013; Sütterlin et al., 2008) might also be a result of the evaluation stage in decision-making. Decision-makers actively devote attention to liked and disliked attribute levels in order to further form the decision.

Therefore, if an alternative receives more attention than another alternative in the evaluation stage, a higher importance of according attributes is probably indicated. As importance is not causal to preference, substitution of choices based on the higher amount of visual attention in the evaluation stage will even downgrade the internal validity of the preference measurement. Accordingly, it is stated:

H1.3: Substitution of behavioral choice with the option that was more attended to in the evaluation stage of preference decision-making will significantly deteriorate the internal validity of preference measurement compared with a purely behavioral preference measurement.

The verification stage reflects a kind of review in which a tentative choice has been made, and a last look at the alternatives finalizes that selection just prior to its announcement (Russo & Leclerc, 1994). As goals loom larger when one moves closer to the goal (Kivetz, Urminsky, & Zheng, 2006; Touré-Tillery & Fishbach, 2011), representations of objects in long-term visual memory that are perceived to be relevant to the goal (“choose the best option”) should be heavily in use at that moment of decision-making. Underpinning that notion, empirical data from Shimojo et al., (2003), and Glaholt and Reingold, (2009b), show that in the last second (approx. 600 ms) before choice, the likelihood that the later choice is looked at rises to a probability of approximately 80%. It is assumed that memory-controlled top-down attention on affirmative, “best” information (not on decision-relevant information, i.e., affirmative and negative information, as in the evaluation stage) dominates the verification stage. The tentative choice (or its attribute levels) is repeatedly and as a final step compared with its best competitors. In the verification stage, visual attention is assumed to indicate pure preferential looking, hence:

H1.4: Substitution of behavioral choice with the option that was more attended to in the verification stage of preference decision-making will significantly improve the internal validity of preference measurement compared with a purely behavioral preference measurement.

Although a closer look at the entire decision duration and distinct stages should provide significant insights, it is assumed that additional subtleties in the time course of decision-making can provide further insights in the process of choice construction (Brownstein, 2003; Wedell & Senter, 1997). In this view, the sequence of information processing in respect of chosen options seems especially interesting. The basic notion is simple: elimination by aspects, as indicated by a gaze bias on the option that is in the end not chosen makes sense in the early stage of decision-making, but not in the late stage of decision-making. The order of an elimination-by-aspects strategy, followed by verification of the later chosen option would reflect a straightforward and effective information processing to achieve the goal of choosing the best option (Billings & Marcus, 1983). This process is hereafter called *process 1* (gaze bias first on the option that does not get chosen, then on the option that does). To test the aforementioned assumption, choices that follow this process 1 characteristic are substituted with the option that received more visual attention in the orientation stage. As presumably eliminated options are then set as choice, the following hypothesis is stated:

H1.5: Substitution of behavioral choice with the option that was more attended to in the orientation stage in a preference decision-making process that follows process 1 (gaze bias first on the option that does not get chosen, then on the option that does) will result in an opposite preference structure compared with a preference structure based on purely behavioral preference measurement.

The difference between hypothesis 1.5 and hypotheses 1.2 is that the specific temporal sequence of gaze bias is additionally regarded. Consequently, the opposite sequence, an early bias on the later choice followed by an elimination-by-aspects strategy, can be regarded as a defective decision process. It is assumed that an early gaze bias on the later chosen option leads to an artificial choice construction (probably in a mere-exposure manner; Zajonc, 2001). This is indicated by an incongruence of visual attention, i.e., "preferential looking," and choice behavior, as more visual attention is devoted to the option that is not chosen shortly before choice. This process is hereafter called *process 2* (gaze bias first on the option that gets chosen, then on the one that does not). The correction of this presumably defective decision process is conducted with a substitution of behaviorally chosen options with the options that gain a higher amount of visual attention in the verification stage in choices that follow process 2 characteristics. As this code of conduct presumably corrects a defective decision process, the following hypothesis is stated:

H1.6: Substitution of behavioral choice with the option that was more attended to in the verification stage in a preference decision-making process that follows the process 2 (gaze bias first on the option

that gets chosen, then on the one that does not) will significantly improve the internal validity of preference measurement compared with a purely behavioral preference measurement.

The difference between hypothesis 1.6 and hypotheses 1.4 is that the specific temporal sequence of gaze bias is additionally regarded.

3.5 Empirical investigation of visual attention in consumer choice

Although visual attention is a well-known indicator for information processing (Rayner, 1998), it has thus far not been applied in the context of discrete choice experiments (DCEs) to explore the stages and processes of consumer decision-making. DCEs are especially useful for this objective, as the exact measurements of preference (utility), as well as the determination of the goodness of measurement, are feasible.

3.5.1 Method

A total of 137 female and 41 male respondents with a mean age of 31.7 years (SD = 5.8 years) participated in the study. Data was collected in online communities with a Web-based survey. All participants conducted a two alternatives forced-choice (2-AFC) discrete choice experiment about shoes with three constitutive independent variables: color, shape, and sole color. Each of the three variables had two attribute levels: shoe color was black or grey, shape was boot or loafer, and sole color was black or white. The overall eight possible options were systematically combined to 12 choice sets with two options in each choice set. Options were combined in choice sets following the principles of Street and Burgess (2004), in order to achieve an orthogonal and balanced discrete choice design that allows estimation of two-way interactions (see Table 1).

Table 1 - Orthogonal and balanced discrete choice design for the study of visual attention in DCEs[2].

	Option 1			Option 2		
Shoes	Color	Shape	Sole color	Color	Shape	Sole color
Choice set						
1	-1	-1	-1	-1	1	1
2	-1	-1	1	-1	1	-1
3	1	-1	-1	1	1	1
4	1	-1	1	1	1	-1
5	-1	-1	-1	1	-1	1
6	1	-1	-1	-1	-1	1
7	-1	1	-1	1	1	1
8	1	1	-1	-1	1	1
9	-1	-1	-1	1	1	-1
10	1	1	1	-1	-1	1
11	-1	1	-1	1	-1	-1
12	1	-1	1	-1	1	1

A choice set started with a forced centralization of the mouse cursor on a fix-cross (duration of 2 sec) in the middle of the screen, so that the gaze was centered between the options when they showed up. There was no time constriction for decisions, and after their choice, respondents received a 10-second rest period (see Figure 3). The presentation order of the 12 choice sets was randomized. After the presentation of the 12 choice sets, a set of questions with reference to demographics and the holdout choice sets (4-AFC ranking task) were presented. Holdout choice sets were used to infer predictive validity of preference elicitation.

[2] Shoe color is coded with 1 for black and -1 for grey. Shoe shape is coded with 1 for boot and -1 for loafer. Sole color is coded 1 for black and -1 for white.

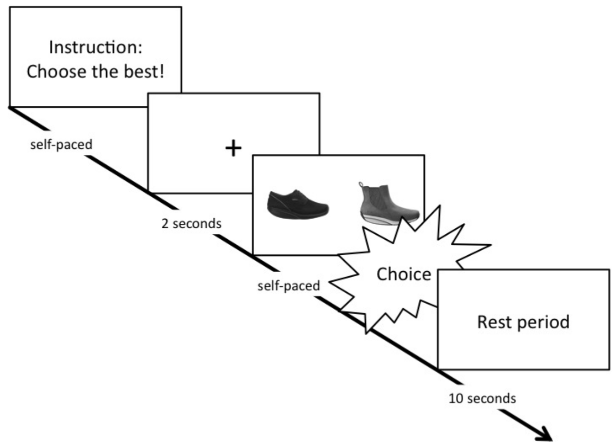


Figure 3 - Course of a choice set with parallel measurement of visual attention.

3.5.1.1 Stimuli

The options to judge and eventually choose were shoes (see Figure 4) described in terms of color (black / brown), shape (loafer / boot), and sole color (black / white). Shoes as a well-known product category were chosen in order to avoid large interindividual differences in product knowledge (e.g., Coupey, Irwin, & Payne, 1998).

Figure 4 - Example choice set of shoes (see Appendix D for the full set of options).

3.5.1.2 Measure of visual attention – mouse clicks

Visual attention was measured with computer mouse clicks, as the discrete choice experiment was conducted online. Reisen, Hoffrage, and Mast (2008) tested computer mouse-based measures against eye-tracking-based measures of visual attention and found that participants searched for the same amount of total information in both conditions (p. 655). Even the pattern of search did not differ between mouse based measures and eye-tracking, which is not supported by other studies concerned with the comparison of process tracing methods (Lohse & Johnson, 1996; van Raaij, 1977). The comparability is nevertheless further supported by empirical evaluations of eye-tracking and mouse-clicking data on photographs, experimental stimuli, and websites, which showed a high overlap between the sampled points (Chen, Anderson, & Sohn, 2001; Cooke, 2006; Egner, Itti, & Scheier, 2000). Computer mouse clicks represent an approximated measure of visual attention, whose accuracy is assumed to be lower than eye-tracking data, but ample for the purpose of this study (focus on alternatives). The advantages of online surveys (large-scale data, high statistical power, easy acquisition, low cost; see Reips, 2000) easily offset minor inaccuracies in data collection.

3.5.1.3 Training

In order to facilitate the indication of gaze with computer mouse clicks, respondents received training prior to the actual examination of clicking behavior in the discrete choice experiment. The training consisted of three steps. The objective of the first training step was to learn to click fast and achieve a click-rate feedback that would provide ample data from click measurement (criterion: minimum of two clicks per second). The second training step objective was the activation of the pointing-gazing connection by clicking on target stimuli (criterion: clicks on all targets). The third training objective was the correct signaling of the participants' preference decision for training stimuli by pushing the respective choice button on the keyboard (1 and 2 for left and right options; criterion: push button). All training steps ended with feedback. If a respondent did not master criteria of a training step, she or he was sent back to the respective training step.

3.5.1.4 Data cleansing – choice exclusion

In order to ensure sufficient gaze data in the choice sample, choices with less than an average of 1 data point per second were excluded from further analysis. Furthermore, choices with one-sided visual attention, and choices with a time to first click higher than 500 ms were excluded. Thus, 1,001 of 2,136 (12 choice sets x 178 respondents) choice observations were not included in the analysis, due to insufficient gaze data. The remaining choice sets were scrutinized in respect to frequency changes across choice sets (1-12) as a check for eventual impacts of the choice exclusion on the balance of the discrete choice design (proportion of stimuli included in the analysis of preferences). The deletion of choices does not significantly impact the balance of considered choice sets (χ^2 (11) = 3.5, n.s.). The final adjusted choice sample shows a mean choice duration of 4.19 sec (SD = 1.6 sec) and a click-rate of 2.08 clicks per second (SD = 0.98). Two clicks per second are a plausible indicator for eye fixations, which have a duration range of up to 500 ms (Rayner, 1998).

3.5.1.5 Ratio for substitution of behavioral choices

Russo and Leclerc (1994) identified three stages of information processing in consumer decision-making in their supermarket shopping study: First, the orientation stage, with a mean time of 3.7 sec; second, the evaluation stage, with 23 sec; and third, the verification stage, with 4.2 sec. Nearly three-quarters of the time spent choosing a product from a shelf display of 16 products was devoted to the evaluation stage. Extrapolating to this 2-AFC study, a time related equilibrium of the stages is assumed, as an evaluation of two alternatives takes considerably less effort than an evaluation of 16 alternatives. The orientation stage was fixed with three clicks, equal to a duration of approximately 1 sec. This means approx. 30% of visual attention was assigned to the orientation stage. The verification stage was fixed to the last second, which makes a mean of 3.2 clicks (SD = 1.4), and therefore 32% of visual attention. The evaluation stage was calculated as residuum of the orientation and verification stage. This stage is characterized by a mean of 3.8 clicks (SD = 4.2). As the evaluation stage was calculated as residuum, 40% of choices had no evaluation stage (475 of 1,135 choices yielded no clicks). When a choice had no evaluation stage, behavioral choice was kept as a dependent variable and was not substituted (relevant for hypothesis 1.3).

For the whole choice duration and for each stage, the gaze bias toward the chosen alternative was analyzed. A gaze bias is calculated as the ratio of clicks on the later choice by the total amount of clicks (in total duration, or in stages). Figure 5 depicts absolute frequencies of observed gaze bias in total decision duration and respective stages.

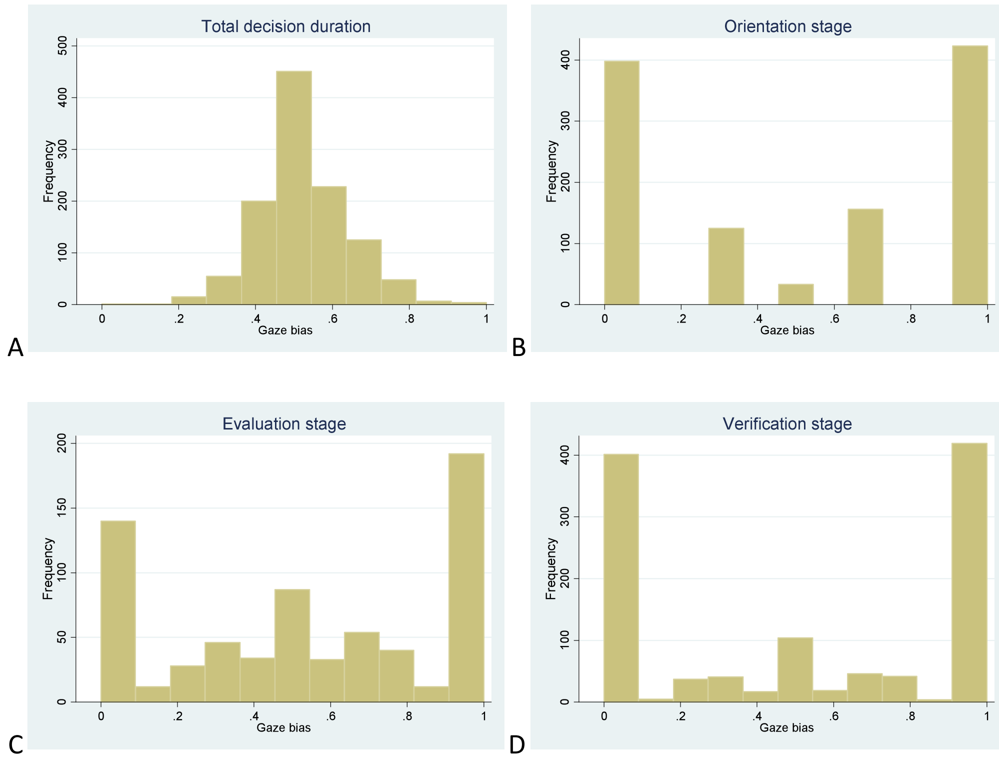


Figure 5 - Gaze bias frequencies in the total choice duration (A), the orientation stage (B), the evaluation stage (C, choice sets without evaluation not considered), and the verification stage (D).[3]

3.5.2 Results

The main instrument for hypothesis testing is the substitution of behavioral choices with choices indicated by visual attention in the total decision duration, orientation, evaluation, and verification stage, and with process 1 or process 2 characteristics. In order to get an impression of the substitution procedure, Table 2 presents the percentage of substituted choices in relation to all choices. Substitution frequencies are around 50%, indicating a comparable frequency of substituted and unsubstituted choices. Only in the evaluation stage is the substitution frequency not around 50% but lower.

[3] Gaze bias frequencies in the total choice duration (A) with M = 0.52 (SD = 0.11), the orientation stage (B) with M = 0.51 (SD = 0.43), the evaluation stage (C, choice sets without evaluation not considered) with M = 0.54 (SD = 0.37), and the verification stage (D) with M = 0.51 (SD = 0.43).[3]

Table 2 - Percentage of substituted choices based on visual attention in decision stages and processes.

	% of substituted choices (all choices = 1,135)
Total decision duration	61%
Orientation stage	49%
Evaluation stage	30%
Verification stage	53%
Process 1	41%
Process 2	45%

Furthermore, as substitutions were based on visual attention data in different stages and processes, it is possible that identical choices were substituted across stages and processes. Table 3 presents the percentages of identical choice substitutions across the total decision duration, stages, and processes of decision-making. Especially substitutions of the orientation stage and process 1, and verification stage and process 2 share a large amount of identical substitutions.

Table 3 - Percentage of identical substituted choices based on visual attention in decision stages and processes.

	Total duration	Orientation	Evaluation	Verification	Process 1
Orientation	67%	--	--	--	--
Evaluation	57%	62%	--	--	--
Verification	46%	13%	35%	--	--
Process 1	59%	92%	69%	6%	--
Process 2	39%	6%	42%	92%	13%

In order to examine the hypotheses, behavioral choice was substituted by the option that attracted more visual attention. Subsequently, a mixed conditional logit model (e.g., McFadden, 1980) was used to analyze the purely behavioral choices and the substituted choices in the total choice duration, the stages and processes, in order to compare the model fit (internal validity), and holdout prediction, predictive validity respectively (see Table 4). The holdout prediction is based on correlations of predicted ranks based on model estimates with empirically derived preference ranks in a holdout task. Hereby, the estimated variance parameters were used as bounds for random draws for the rank prediction. The presented holdout prediction values represent the mean correlation of 1,000 draws (comparable to the Monte Carlo simulation, Mooney, 1994).

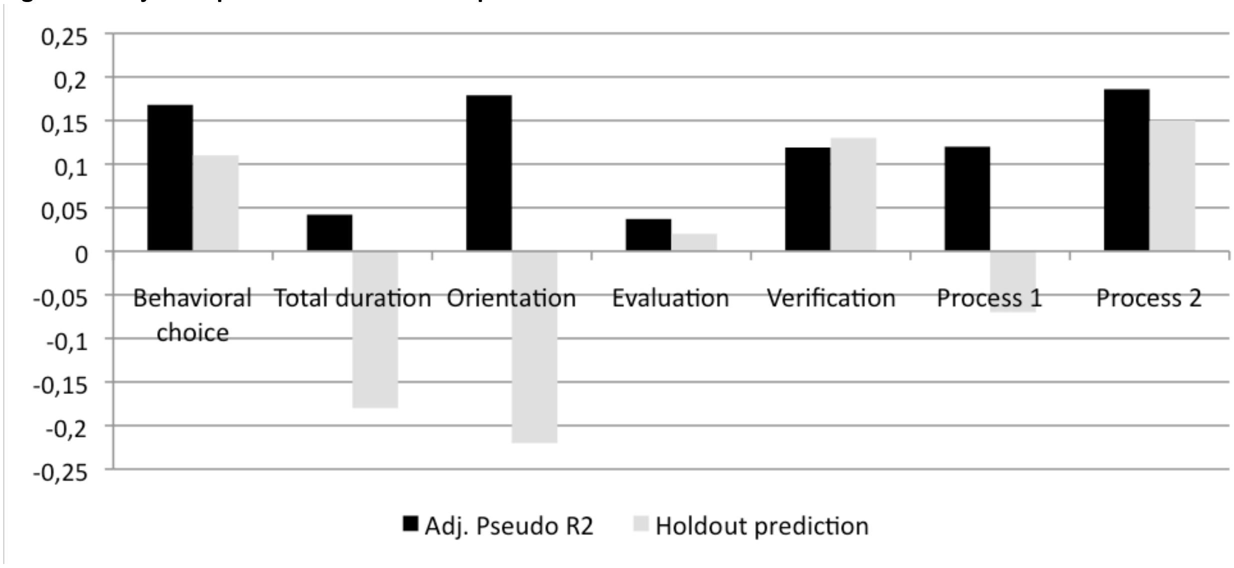
Table 4 - Results of mixed logit regressions with behavioral and substituted choices based on visual attention.

	Behavioral choice		Total duration		Orientation		Evaluation		Verification		Process 1		Process 2	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Color – BROWN	.112	.102	-.004	.049	**-.124****	.05	.011	.055	.071	.050	**-.107***	.053	.082	.049
Color – BLACK	-.112		.004		**.124****		-.011		-.071		**.107***		-.082	
Shape – BOOT	**-.733*****	.165	**.268*****	.062	**.329****	.123	-.003	.070	**-.192***	.090	.112	.095	**-.429****	.122
Shape – LOAFER	**.733*****		**-.268*****		**-.329****		.003		**.192***		-.112		**.429****	
Sole – WHITE	.032	.075	**.109****	.048	.034	.047	.003	.043	.009	.044	.014	.045	-.006	.047
Sole – BLACK	-.032		**-.109****		-.034		-.003		-.009		-.014		.006	
Color X shape –DIFF.	-.034	.077	-.008	.051	.006	.061	-.047	.049	-.009	.051	.021	.053	.012	.062
Color X shape – SAME	.034		.008		-.006		.047		.009		-.021		-.012	
Color X sole – DIFF.	**-.222*****	.067	-.027	.045	-.017	.058	-.064	.047	-.054	.051	-.027	.053	-.079	.058
Color X sole – SAME	**.222*****		.027		.017		.064		.054		.027		.079	
Shape X sole – DIFF.	.012	.061	-.012	.043	.016	.048	.032	.044	.021	.045	-.035	.046	-.027	.048
Shape X sole – SAME	-.012		.012		-.016		-.032		-.021		.035		.027	
Variance parameters														
Variance color	**.958*****	.264	.088	.051	.023	.044	**.176****	.065	.084	.051	.111	.058	.018	.044
Variance shape	**2.31*****	.620	**.233***	.078	**1.23*****	.346	**.419*****	.119	**.615*****	.170	**.814*****	.221	**.975*****	.273
Variance sole	.195	.101	.062	.045	.001	.006	.005	.023	.001	.003	.002	.002	.001	.003
Variance color X shape	**.333***	.134	**.115***	.056	**.178***	.080	.089	.050	.079	.053	.095	.056	**.197***	.085
Variance color X sole	.001	.010	.004	.029	.027	.049	.007	.037	.014	.041	.021	.043	.024	.048
Variance shape X sole	.002	.015	.001	.015	.011	.031	.001	.006	.001	.002	.001	.001	.009	.031
Statistics														
LN-Likelihood	-642.16		-741.71		-633.71		-745.49		-680.72		-680.46		-628.09	
BIC	1368.73		1567.83		1351.83		1575.39		1445.83		1445.33		1340.59	
Adj. pseudo-R^2(0)	.168		.042		.179		.037		.119		.120		.186	
Holdout prediction (ρ)	0.11 (SE <.001)		-0.18 (SE <.001)		-0.22 (SE <.001)		0.02 (SE <.001)		0.13 (SE <.001)		-0.07 (SE <.001)		0.15 (SE <.001)	
No. of parameters	12		12		12		12		12		12		12	

(*** = p < .001; ** = p < .01; * = p < .05)

As all choice models have the same number of estimated parameters (12) and data points (n = 1,135), the log-likelihood measures and BIC (Bayesian Information Criterion) can be used for direct model-fit comparison. The choice model based on process 2 specifications is indicated as the best-fitting model, followed by the orientation model, the behavioral model, the process 1 model, the verification model, and lastly, the total duration model. Figure 6 provides an overview of the internal validity (adjusted pseudo-R^2) and the predictive validity (holdout prediction) of all estimated choice models.

Figure 6 - Adjusted pseudo-R^2 and holdout prediction for all estimated choice models.



Contrary to expectations, the substitution of behavioral choice with the option that received more visual attention during the total decision duration did not improve internal or predictive validity. Compared with the behavioral choice model, the total duration model shows a significant drop in internal validity (difference of pseudo-R^2 = 12.6). This result is also supported by BIC-values, which indicate the meaningfully worse model-fit of the total duration model (BIC-Behavioral: 1368.73 vs. BIC-Total duration: 1567.83, the smaller the BIC-value, the better the model-fit; Kass and Raftery, 1995) suggest that differences in BIC higher than 2 points can be considered meaningful). The difference regarding predictive validity is even larger. Here, the total duration model results in a negative correlation with the holdout ranks (ρ = -.185). Based on these results, hypothesis 1.1 (gaze bias in total decision duration) cannot be confirmed.

In comparison of the preference estimates of the behavioral model with the model based on visual attention in the orientation stage, two sign reversals with regard to the three main effects can be observed. The preferred shape of shoes as well as the preferred color in the orientation model contradicts the according parameters of the behavioral model. Furthermore, the negative correlation of predicted with empirical holdout ranks is highly negative (ρ = -.23), suggesting a contradicting predicted (empirical) preference structure. Thus, hypothesis 1.2 (gaze bias in orientation stage) is largely confirmed.

Internal validity of the model based on choices with more visual attention in the evaluation stage is near to zero (pseudo-R^2 = .037). Compared with the behavioral choice model the model-fit of the evaluation model is meaningfully worse (BIC-Behavioral: 1368.73 vs. BIC-Evaluation: 1575.39). This suggests that the derived choices are not related to the explanatory variables in terms of preference (choice). Furthermore, the holdout prediction is also near zero (ρ = .015), and thus supports this notion. Compared with the behavioral model, a meaningful deterioration of internal validity can be observed. Thus, hypothesis 1.3 (gaze bias in evaluation stage) can be confirmed.

Log-likelihood and adjusted pseudo-R^2 indicate that the verification model (options with more visual attention in the verification stage were set as choice) does not show an improved internal validity compared with the behavioral model. In fact, the verification model performs significantly worse regarding internal validity (BIC-Behavioral: 1368.73 vs. BIC-Verification: 1445.83). For predictive validity (ρ) there are no meaningful differences between the two choice models (0.124 vs. 0.127). Based on these results, hypothesis 1.4 (gaze bias in verification stage) cannot be confirmed.

Comparable to the orientation model, the process 1 model, in which an early gaze bias is assumed to indicate eliminated options, shows two sign reversal on main attributes of the stimuli (color and shape) compared with the behavioral choice model. Although only one of these sign reversals is actually significant (color), a contradicting preference structure is suggested, which is further underpinned by the negative holdout prediction measure (ρ = -.072). Thus, hypothesis 1.5 (gaze bias in process 1 choices) is largely confirmed.

The substitution of the behavioral choice that follows process 2 characteristics (gaze bias first on the option that does get chosen, then on the one that does not) with the option that was more attended to in the verification stage results in the best-fitting model with the best predictive performance. The additional integration of the temporal sequence of gaze bias in the process 2 model outperformed all other choice models. Compared with the behavioral choice model, the process 2 model provides a significantly better model-fit (BIC-Behavioral: 1368.73 vs. BIC-Process 2: 1340.59). Pertaining to predictive validity, the process 2 model predicts the holdout rankings with 15%, compared with the behavioral model, which achieves 11%. It is important to note that the substitution of choice with the option that received more visual attention in a process 2 choice is assumed to correct a potentially defective decision process (gaze bias first on that option that does get chosen, then on the one that does not). As this correction leads to the best performing model, hypothesis 1.6 (gaze bias in process 2 choices) can be confirmed.

3.5.3 Discussion

The substitution of behavioral choices with the options that gained more visual attention in varying stages of the decision process allowed a closer look at the cognitive processes during consumer decision-making in a discrete choice context. The analytical results were mainly in line with expectations. In particular, they suggest that it is feasible and reasonable to substitute behavioral data with visual attention data. Thus, results bolster the assumption of Pieters and Warlop (1999) that "choice can be predicted from observations of visual attention patterns only" (p. 14).

Interestingly, results of this study do not support this notion in general, as the substitution of behavioral choice based on the total decision duration did not improve internal and predictive validity. Visual attention in the total decision duration seems to reflect differing cognitive processes that could have mutually evened out the indicative power of gaze bias. More visual attention in consumer choice therefore does not always stand for preferential looking (Birch, Shimojo, & Held, 1985) but might also indicate more fine-grained cognitive processes in the course of decision-making. This notion is supported by estimation results of choice models that focus on visual attention in differing stages of decision-making (Russo & Leclerc, 1994). The low internal validity of the total duration model also suggests that constructive processes might take place during decision-making, which are most likely attributable to the evaluation stage that also yields low internal and predictive validity. Thus, one reason for the lack of predictive power (in terms of preferential looking) in this study could be the implicitly demanded trade-off in discrete choice experiments. As DCEs are designed to induce a tradeoff, respondents might have had a stronger focus on the evaluation of alternatives compared to other consumer choice paradigms (Pieters & Warlop, 1999).

The orientation stage is not expected to be involved in constructive decision processes, as very fast selective attention processes are assumed in this stage (Milosavljevic et al., 2011). This assumption is supported by the relatively high internal validity. The meaningful yet opposing holdout prediction, as well as sign reversals on main attributes, points to the decision strategy in use during orientation: elimination by aspects (in line with e.g. Billings & Marcus, 1983). Thus, substitution of behavioral choice with the option that received more attention uncovers the strong top-down influence, even in this initial and very short decision stage.

The presumed effortful cognitive processes in the evaluation stage, however, are prone to constructive decision processes. The lack of internal and predictive validity of the choice model based on visual attention in this stage supports this assumption. The different possible strategies in this stage (e.g., conjunctive, disjunctive, satisficing; see Harte & Koele, 1995), and the very likely regress on (error-prone) memory, are key factors for this aptitude (Weber & Johnson, 2000). Furthermore, visual attention is assumed to reflect importance and not preference (Van Raaij, 1977, Reisen, Hoffrage, & Mast, 2008). Hence, substituted choices based on visual attention indicate the trade-off process rather than preferential looking. A limiting factor concerned with this stage is the lack of evaluation in 40% of observations. Although the decision task with just two alternatives to choose from could have resulted in this finding (i.e., respondents combined orientation and evaluation / evaluation and verification), future research should develop clear indicators for the start and the end of a possible evaluation stage (e.g., Russo & Leclerc, 1994). Subsequently, future research should disentangle strategies-in-use and memory effects in order to test their particular impact on probable constructive processes in an evaluation stage.

Whereas the cognitive processes of the evaluation stage remain unknown, the cognitive process taking place in the verification stage is more straightforward. It is strongly suggested that the tentative choice receive a last check prior to announcement in this stage (Russo & Leclerc, 1994). The assumedly strong impact of memory-controlled top-down attention in this stage, which should reflect preferential looking, was not found in this study. Internal and predictive validity did not improve when substituting behavioral choice with the option that received more visual attention in the verification stage. On the one hand, it could be possible that there is not much to verify in a choice set with two alternatives. On the other hand, visual attention during verification, which is a finalizing evaluation, could partly reflect importance, comparable to the evaluation stage. Future research could use a methodological setup with conditions containing a varying number of alternatives, and a clear distinction between evaluation and verification to yield further insights in these two stages of decision-making.

Besides stages of decision-making, the time course of decision-making is assumed to provide further insights into the process of consumer choice. Thus, the visual attention in the beginning (orientation) and the end (verification) of decision-making received a combined consideration. Process 1 describes choices in which respondents first look longer on the option that does not get chosen, and then longer on the option that does. This code of conduct is considered as simple and effective decision-making: First, unwanted aspects are eliminated, and then wanted aspects are verified. Thus, the substitution of behavioral choice with the option that received more attention in the orientation stage should yield an opposite preference structure, as probably eliminated options are set as choice. This is confirmed by the analysis (two main effects with sign reversals, and a negative holdout prediction). The substituted choices in process 1 and orientation stage show an overlap of 92%; thus, these two substitution patterns are very similar. However, the 8% (91 choices of 1,135 choices) difference seems to make a substantial contribution. In a comparison of the orientation model with the process 1 model, the orientation model shows a meaningfully better model fit, and a lower predictive validity. This implies that the orientation stage alone is more indicative for the decision strategy in use (EBA) than the process of decision-making. Thus the consideration of processes did not yield additional insights in this case.

With regard to process 2 (an early bias on the later choice followed by a focus on unwanted attributes), there are meaningful additional insights. Although substituted choices in the process 2 model and verification model are 92% identical, the difference in internal and predictive validity seems meaningful. The substitution of behavioral choice in choices that followed a process 2 with options that received more visual attention in the verification stage yields significant improvement. Thus, by substituting the behavioral choice, a probably defective decision process is corrected by use of visual attention. Consciously or unconsciously, respondents probably did not express their "true" preference in the behavioral choice, which is indicated by the process of visual attention. The substitution led to congruence between choice and a visual decision process that was often observed: a growing gaze bias towards the chosen option (e.g., Shimojo et al, 2003). This indicates that the process of a growing gaze bias for the option that was eventually chosen indicates a non-defective decision process, which is presumably not influenced by preference construction.

3.6 Summary and outlook of visual attention in consumer decision-making

Previous research focused on the role of visual attention across the entire time span of supermarket-like consumer choices. Participants had to choose from differing products but not from systematically combined alternatives as in DCEs. The focus of this work goes beyond the observation of visual attention in unspecific decision tasks across the whole time span of decision-making. This work focuses on carefully designed consumer decisions and additionally focuses on visual attention in different stages and processes of consumer choice. The use of discrete choice experiments (Louviere & Woodworth, 1983) as paradigm to observe consumer choice allowed the estimation of utility on the attribute level, and thus internal and predictive validity of preference elicitation with and without integration of visual attention.

Generally speaking, there are three take-aways from this exploration of visual attention in DCEs. First, the additional measurement of visual attention is a promising approach to gain a deeper understanding of consumer choice - not across the total decision duration, but in particular stages. The integration of visual attention in preference analysis by substitution of behavioral choices with options that were more attended to yields important insights about the cognitive processes taking place during decision-making.

Second, the substitution of behavioral choices in line with process 2 (first more attention on the option that does get chosen, later on the option that does not) implies that this process seems to indicate a window to flawed preference construction. As this substitution makes the choice fit in a process 1 characteristic (first more attention on the option that does not get chosen, then on the option that does), process 1 could indicate a window into the master list of preference. This notion is also supported by a vast amount of research that repeatedly finds exactly the same process 1 pattern in most preference decisions (Shimojo et al., 2003; Glaholt & Reingold, 2009, Kraijbich et al., 2011).

Third, measuring visual attention with mouse clicks seems feasible and reasonable. Although the accuracy is considerably lower compared with eye-tracking, the advantages of online surveys (large-scale data, high statistical power, easy acquisition, low cost; see Reips, 2000) could offset inaccuracies in data collection.

Choice models based on behavioral choice and visual attention in stages of decision-making do not only vary in their internal and predictive validity but also uncover differing preference structures. These differences might yield important insights for product development, for example. The additional source of information based on visual attention allows taking a look at basic cognitive processes during decision-making that could also take place in real shopping contexts (in supermarkets, for example). Based on the behavioral choice model, there is a significant main effect (shape of shoes), as well as a significant interaction effect (color of shoe and color of sole). Considering the process 2 model (best-fitting model with a possible correction of preference construction), only the main effect, “shape of shoe,” is meaningful. Furthermore, meaningful variance of preference is limited to two explaining variables (shape, and the interaction of color and shape) in the process 2 model, compared with more taste heterogeneity in the behavioral model (additional heterogeneity in the main effect color). Further consideration of the choice model based on visual attention (process 2) could therefore yield important information for the development of optimal products. Especially in relation to fast-moving consumer goods, in which consumer evaluation is presumably low, this basic psychophysiological window into the cognitive processes might yield a more suitable picture of the actual needs of customers.

A limiting factor for the practical relevance of the findings is the difference in holdout prediction of the behavioral and the process 2 choice model, which is rather low (0.04, whereas a level of 0.1 would indicate meaningfulness; see Cohen, 1992). The response mode of the holdout prediction task (ranking) differed from the response mode of the preference elicitation task (choices). Changes in response mode can already lead to preference construction (Payne, Bettman, & Schkade, 1999a; Schkade & Johnson, 1989), which possibly masked effects concerned with visual attention. In order to control for effects of response mode, future research should use the same response mode in the holdout prediction task and in the preference elicitation task. A further control of probable effects of visual attention on preference construction in the holdout task would complete a sound testing of predictive validity.

Based on the promising approach of this study, future research is encouraged to further tackle the challenge of integrating visual attention in decision processes. Especially auspicious for additional insights are models of visual attention that focus on drift-diffusion (Ratcliff & McKoon, 2008), which closely resembles the utility of options (Towal, Mormann, & Koch, 2013).

4 Affective valence in consumer decision-making

Affect is defined as "simple primitive non-reflective feeling most evident in mood and emotion" (Russell & Barett, 2009, p. 104). The fundamental role of affect in decision-making has been acknowledged for more than two decades (Mellers, Schwartz, & Ritov, 1999) and is still receiving ever-greater attention (Naqvi, Shiv, & Bechara, 2006; Pfister & Bohm, 2008).

A popular perspective is that decision-making is a rational process that does not need affect, and affect even disrupts the rational process. Rationality is mostly understood as formal consistency (procedural and descriptive invariance), conforming to the laws of probability. In that sense, rationally behaving people make optimal choices. Contradictory evidence is accumulating, however, and points out that decision-making without affective involvement might, in some cases, be suboptimal, or not even possible (Bechara, Damasio, Tranel, & Damasio, 1997). Evidence from neuropsychological studies supports that notion by showing that the separate structural or functional localization of cognition (rationality) and affect in the human brain might not be feasible (Phelps, 2006).

4.1 Functions of affective valence

Many researchers have acknowledged affective valence and its information function, though under different perspectives (Clore, Schwarz, & Conway, 1994; Schwarz & Clore, 1988; Slovic, Finucane, Peters, & MacGregor, 2002). The information implicated in affective valence is used to evaluate and to construct preference, i.e., to make a decision.

In Schwarz's and Clore's affect-as-information framework (1988), positive and negative valences are understood to provide information about evaluative judgments, for example, about one's own life satisfaction. The impact of information on decision-making is also prominent when the affective valence can be attributed to an unrelated event that is not part of the decision problem and is labeled incidental affect (Loewenstein & Lerner, 2003).

In contrast with Schwarz's and Clore's (1988) perspective, which focuses primarily on incidental affect, Mellers (2000) proposed a theory that is based on integral, directly decision-relevant affect. The decision affect theory (Mellers, 2000) focuses on the pleasure or displeasure that arises directly from the choice options and their consequences under consideration. Precisely formulated, it is assumed that decision-makers compute a weighted sum of anticipated pleasures based on the expected outcomes of risky choices. The option with what is assumed to be the highest amount of pleasure is chosen. Thus, pleasure, which informs the decision-maker about the expected utility of a consequence, is seen as a substitute of utility. This interpretation of utility as pleasure is in line with the very basic origin of the utility concept (Bernoulli, 1954).

Slovic et al. (2002) proposed a somewhat related approach, which is independent from the issue of integral or incidental affective valence: the affect heuristic. This approach suggests the reliance on one's immediate affective experience of liking or disliking something in the course of evaluation. The affect heuristic is a quick and simple process that ideally refers to the affect elicited by the respective decision problem, but it can also be caused by intrusions from unrelated external or internal events (e.g., memories).

Regardless of the focus on integral or incidental affect, these theories consider affect to be information that is essential for the process of evaluation in decision-making. They agree that affect acts as a one-dimensional process, whereas qualitative subtleties of affect are not considered. The possible multitude of affective experiences is projected on one dimension of pleasure and pain (Pfister & Böhm, 2008, p. 9). This valence dimension is assumed to represent a core feature of an affective experience (Barrett, 2006). To the extent that affect can be transferred to a one-dimensional pleasure-pain scale without loss of meaning, they serve as informative signals for the decision-maker. Pfister and Böhm (2008) call these emotions reducible emotions, which can be considered a general class of orientation feelings with respect to preferences (Norman, Price, & Duff, 2006). As decision-relevant integral affect first has to be inferred from the decision problem before it can function as evaluative information, the process of affect inference receives a closer look in the following section.

4.2 Process of affect inference

The notion of affect as information for evaluative judgments is appealing, but upon closer consideration, such a hypothesis is not logical. Why should affective valence yield information about evaluations and not vice versa? It should be much more plausible that evaluations generate affect. When observing yogurts with the goal to buy yogurt, appraisals of the features should take place first (strawberry taste, low fat, and organic label are good), before the decision-maker feels the affect associated with that specific yogurt (pleasure).

Appraisal theories of affect provide a plausible and straightforward approach to the question of how integral affect is inferred from information about eliciting events (Schwarz & Clore, 1988). The appraisal mediation hypothesis suggests that the inference of affect from situational information (a product) proceeds in two steps: First, one infers the likely appraisals of that event (matching situational features to typical appraisals) and then the concomitant affect on the basis of the inferred appraisals (matching of appraisal to affect concepts). Several studies (Reisenzein & Hofmann, 1990; C. A. Smith & Lazarus, 1993) confirm the appraisal mediation hypothesis, in particular with findings that inferred affect is frequently accompanied by fitting evaluative characteristics. However, the appraisal mediation hypothesis conflicts with reaction-time data.

If affect was generated as the appraisal mediation hypothesis suggests, then affective inferences are necessarily more complex than evaluative inferences in the sense that they require more processing steps. As complex inferences (affective inference) should take more time than the inferences they comprise (appraisal inference), the appraisal mediation hypothesis predicts that affective inferences take longer than appraisal inferences. However, studies designed to test this prediction have consistently failed to support it (Siemer, 2001; Siemer & Reisenzein, 2007). Siemer (2001) found that affective judgments were made faster than appraisal inferences.

Siemer and Reisenzein (2007) suggest an approach to solve this problem, which is plausible in a cognitive psychology perspective (J. R. Anderson, 2005) and in a neuropsychological perspective (Ledoux, 1989). They suggest a proceduralization process that accounts for fast affective inferences. Although inferred appraisals initially mediate affective inferences, the latter become proceduralized or automatized as a result of being widely practiced (J. R. Anderson, 2005). It is assumed that the intermediate steps of a proceduralized inference process (here: appraisal inference) are unconscious and fast. Anderson (2005) suggests that intermediate steps can gradually be erased through knowledge compilation. In contrast with dual-process models of cognition (E. R. Smith & Neumann, 2005), which view automatic and deliberate processes as independent, the proceduralization account allows a transition from controlled to automatic processing.

In two experiments, Siemer and Reisenzein (2007) confirmed the proceduralization hypothesis. Appraisal inferences were made faster in experimentally induced affective judgments (guilt, anger, pity, gratitude), compared with mere appraisal judgments, such as event evaluation (Experiment 1). Experiment 2 replicated this finding with a control for the mere activation of affective concepts due to stimulus exposure as a possible but ruled-out influence of the facilitation of affective judgments. Affective valence in consumer decision-making can thus be seen as hard-wired information that facilitates the evaluation process. The following section examines research concerned with the use of affective valence for decision research.

4.3 Anticipated valence in decision-making

There is growing evidence that choices vary with anticipated affect (Mellers, 2000). However, these inferences are often indirect, as the functional forms of anticipated affect are often mathematically formulated, yet without any direct empirical assessment of affect. Research over the past decade has tried to fill this empirical gap.

Mellers, Schwartz, and Ritov (1999) started with the direct assessment of anticipated affect and choice in a series of gambling tasks. Participants were presented with pairs of gambles, which were displayed as pie charts on a computer screen. In each trial, participants chose the preferred gamble. A spinner attached to the center of the preferred gamble began to rotate. Eventually, the spinner stopped in a region and pointed to a hypothetical outcome. Participants rated the pleasure they would feel if the outcome had been real on a category rating scale from positive to negative affect. Findings suggest that, as wins increase, anticipated pleasure increases.

In a series of subsequent studies, Mellers et al. (1999) generalized their findings in terms of temporal and contextual differences. The crucial question leading their research was the accuracy of subjectively expected pleasure forecasts. If decision-makers actually base their choice on subjectively expected pleasure, then accuracy should be high across temporal and contextual different studies. Thus, the studies differed in two respects: duration and decision contexts. The time between judgments varied considerably. In a pregnancy study, women waiting for the results of their pregnancy test judged the anticipated and actual pleasure of test results, which were made approximately 10 minutes apart. In gambling and dieting studies, judgments were made approximately one week apart. And in a grading study, anticipated and actual pleasure were assessed four months apart. Obviously, pregnancy, dieting, gambling, and grades constitute very differing fields of life concerned with more or less anticipated affect. Findings of this study indicate that anticipated and actual affect were judged quite similarly, and anticipated affect thus constituted an adequate forecast. Nevertheless, actual pleasure was often higher than anticipated pleasure (Mellers, 2000, p. 919).

Systematic errors of hedonic forecasts have been identified quite early (Loewenstein & Schkade, 1999). Affect can have unexpected influence on perception, attention, and information processing and can range from boredom to overwhelming visceral states (Loewenstein, 1996). Joyful people usually overestimate the chance of favorable outcomes, whereas sad people overrate the probability of unfavorable outcomes (Nygren, Isen, Taylor, & Dulin, 1996). Happy people are better at retrieving happy memories, and when sad, they are better at retrieving sad events (W. F. Wright & Bower, 1992). People also have a tendency to project immediate feelings onto memories, which can lead to the overestimation of affect. McFarland and Ross (1987) assessed the romantic feelings of couples at the beginning of their relationship and two months later. Those whose feelings became more negative over time overestimated their initial bad feelings. Those who felt more positive over time overestimated their initial good feelings.

4.4 Immediate affective valence – somatic markers

As the amount of possible systematic errors with respect to the forecast of anticipated affect is vast, it might be more useful to consider immediate affect, in the sense of an immediate heuristic for decision-making (Slovic et al., 2002). The first researcher to describe affect as a heuristic means was Wright (1975), who proposed the affect-referral heuristic. This mechanism influences the choice of a product by the remembered affect associated with it (Pham, 1998). This claim was based on the notion that attitudes have a strong evaluative component (e.g., Thurstone, 1928). Thus, people are assumed to rely on feelings they experience as they hold the evaluated object in their mind rather than computing evaluations from attributes (Pham, 1998).

This assumption was supported by experiments of the neurologist Antonio Damasio (1994). He derived his somatic marker theory from observations of patients with damage to the ventromedial frontal cortices of the brain. This damage has left their basic intelligence, memory, and capacity for logical thinking intact but has impaired their ability to use feeling as information for judgment. Persons suffering this damage became socially dysfunctional, as people's ability to make decisions that are in their best interest was destroyed (Bechara et al., 1997). In an attempt to understand the mechanism of "good" decision-making, Damasio argues that thoughts are mainly made up of images, but they also include sounds, odors, visual impressions, ideas, and words. A life-long learning history leads these images to become "marked" by positive and negative feelings linked to somatic or bodily states. These somatic markers are "feelings generated from secondary emotions. These emotions and feelings have been connected, by learning, to predicted future outcomes of certain scenarios" (Damasio, 1994, p. 174). A negative somatic marker, which is linked to an image of an anticipated outcome, constitutes an alarm. A positive marker becomes a signal of incentive. Damasio (1994) concluded that somatic markers increase the accuracy and efficiency of decision-making, whereas their absence impairs decision-making performance.

Damasio (1994) tested the somatic marker hypothesis in a decision-making experiment whereby participants had the task to select cards from any of four decks. Turning a card from a deck resulted in the gain or loss of a sum of money, as revealed on the back of the card. Two decks provided large payoffs but also the possibility to lose a large sum; in the long run, these decks led to a loss. The other two decks provided lower gains but also lower risks of losing, and they were designed to provide a sustainable gain. Normal subjects and patients with brain lesions outside the prefrontal area learned to avoid decks with eventually catastrophic losses, patients with frontal lobe lesions did not and thus lost a lot of money. Although patients with prefrontal lobe lesions reacted normally to gains and losses when they occurred (high arousal measured with skin conductance), they did not experience anticipatory affect when thinking about choices from one of the four decks. They failed to show proper affective anticipatory responses, even after numerous opportunities to learn them.

As preferences are formed over a life-long history (L. L. Birch, 1999), consumers have numerous opportunities to develop somatic markers for approach and avoidance. Both negative and positive affect, should serve as somatic markers during a choice. Positive affect in consumer decision-making should therefore indicate possible incentive attributes, and negative affect indicates attributes that should be avoided. In the sense of markers, negative and positive affect is functional. Consequently, the existence of positive and negative valence during decision-making indicates the existence of somatic markers and thus the probable stability of the expressed choice (Lee, Amir, & Ariely, 2009; Pham, Cohen, Pracejus, & Hughes, 2001).

Lee et al. (2009), for example, conducted a series of experiments in which the reliance on affect was manipulated by either showing names of products (smaller reliance on affect) or pictures of products (higher reliance on affect). Results consistently showed that choices with presumably higher reliance on affect produced less transitive choices, thus suggesting higher measured preference stability. Although these experiments were carefully designed, it is questionable that reliance on affect was really manipulated, as no manipulation check was conducted, and the name-picture manipulation might as well have changed the decision strategies in use. As a further scrutiny of the somatic marker hypotheses in consumer decision-making, the study in this dissertation relies on actual experienced affect. In line with Damasio (1994) and Lee et al. (2009), the following hypothesis is stated:

H2.1: Experienced affective valence (positive or negative) during choice indicates the existence of somatic markers, which results in the higher internal and predictive validity of preference measurement.

4.5 Effects of affect on cognitive processes

As far as the analysis and forecast of consumer choice are concerned, the interrelation of cognitive processes and immediate affect is especially interesting. Positive affect can promote more flexible and creative problem solving (Ashby & Isen, 1999), and some negative moods can lead to greater analytical thinking (M. F. Luce, 1998; M. F. Luce, Bettman, & Payne, 1997). A large body of research documents that individuals in a happy mood are more likely to show a heuristic processing strategy. This strategy is characterized by an increased dependence on pre-existing knowledge and rather little devotion to details of the decision problem. By contrast, people in a sad mood tend to adopt a more systematic processing approach with high attention to the relevant details and little reliance on pre-existing knowledge (for a review, see Schwarz & Clore, 1996). These differences have been documented across a broad range of domains, such as the processing of persuasive messages (Schwarz, Bless, & Bohner, 1991), the use of stereotypes (Bodenhausen, Kramer, & Süsser, 1994), and the reliance on scripts for behavioral sequences (Bless et al., 1996). These differences in processing styles probably reflect that information processing is tuned to meet the needs of an actual situation, which at least partially happens by signaled affective states (Schwarz, 1990). Thus, negative affect might signal that a particular decision is somewhat challenging, and a processing style that pays close attention to the specifics of the situation is elicited. However, positive affect signals an unproblematic situation that allows people to rely on their usual routines and pre-existing knowledge structures (Schwarz & Clore, 1996).

During decision-making with negative affect, systematic processing might yield consistent and thus internally valid decisions, but the missing reliance and pre-existing knowledge could also impair the stability of choices and thus predictive validity. During decision-making with positive affect, heuristic processing might lead to inconsistency, but the predictive validity could improve due to reliance on pre-existing knowledge (e.g., Loewenstein & Lerner, 2003). Thus, it is stated:

H2.2: Consumer choices with relatively more experienced negative affect will result in higher internal validity but lower predictive validity. By contrast, consumer choices with relatively more experienced positive affect will lead to lower internal validity but higher predictive validity.

4.6 Positive and negative valence – two dimensions

To date, the perspective on affective valence has been one-dimensional with positive valence on one end of the dimension, and negative valence on the other end. Cacioppo and Berntson (1994) suggest that this perspective might be a historically founded oversimplification. They developed an alternative approach that accounts for co-activity of positive and negative affect: the evaluative space model (ESM, Cacioppo, Gardner, & Berntson, 1999). Although behavior is constrained to a single bipolar dimension of approach and avoidance (choosing / rejecting), the underlying affect system assumedly is not. The ESM proposes that behavior is the ultimate output of the affect system, which is defined by operating characteristics that differ for both positivity and negativity. As positive and negative affect is functionally separable and partially independent, increasing one is not assumed to have a direct effect on the other. Imagine a consumer who receives more and more positive and negative information about her favored product (e.g., organic ingredients have less taste). Traditional models of affect would suggest that the consumers' feelings will not only become more negative, but also less positive (reciprocal activation). The ESM suggests that an increase in negativity is not necessarily accompanied by a decrease in positivity. Positivity might be maintained as negativity increases, resulting in co-activation. This feature is the hallmark of the ESM, as it provides a theoretical basis for objective ambivalence (Norris, Gollan, Berntson, & Cacioppo, 2010).

The experience of ambivalence in ecologically valid situations is strong evidence for the co-activation of positivity and negativity. Such field settings, however, often sacrifice experimental control for psychological impact. Larsen, McGraw, Mellers, and Cacioppo (2004) elicited ambivalence in the laboratory environment via a unique set of gamble outcomes in which winning (or losing) the lesser of two amounts (e.g., $5 instead of $10) reliably produced simultaneous happiness and sadness. Disappointing wins (and relieving losses) have proved to be useful tools for studying the experience of ambivalence in the laboratory and have been used to validate the evaluative space grid (ESG), a new measure of affect that directly follows from the theoretical predictions of the ESM (J.T. Larsen, Norris, McGraw, Hawkley, & Cacioppo, 2009).

The other extreme of the co-activation of positive and negative affect would be the mutual non-presence of negativity and positivity, resulting in indifference (Cacioppo & Berntson, 1994). Whereas the effects of indifference on consumer decisions are quite clear (i.e., random choice behavior), the effects of ambivalence are more subtle. Nowlis, Kahn, and Dhar (2002) examined the effects of ambivalence in a series of experiments. Excluding a neutral response option induced ambivalence. Results suggest that ambivalence led to more extreme judgments, less compensatory choices, and greater risk aversion. Thus, it is stated:

H2.3: High (low) positive *and* negative affect during consumer choices indicates ambivalence (indifference), leading to less internal and predictive validity, compared with more positive *or* negative affect, or medium levels of positive and negative affect.

As shown above, affective valence does not only have a presumably important information function (E. Peters, 2006) but also might have differentiated effects on the process and outcomes of consumer decision-making.

4.7 Empirical investigation of affective valence in consumer choice

The objective of the second empirical study in this work (the first empirical study relates to visual attention in consumer decisions) is the exploration of affect in consumer decision-making. Trade-off and selective attention mechanisms of affect, in particular, presumably deliver important insights (e.g., Peters, 2006). Thus, immediate affective valence and affective arousal are captured during decision-making in DCEs by means of facial electromyography (fEMG, valence), and skin conductance response (SCR, arousal). As fEMG and skin conductance measures do not disturb each other by any means (skin conductance is captured on the palm and EMG on the face), they are measured in parallel in this second study. The general methodological setup of study 2 will be detailed in the following subsection, and can be assigned to all empirical reports following this chapter. Only the methods used to capture valence (via fEMG) and arousal (via SCR) are different from each other and will be explicated in chapters 4.7.1 (fEMG) and 5.4.1 (SCR).

4.7.1 Method

Forty-nine students of the University of Hamburg who responded to posted flyers or e-mail invitations participated in this laboratory study for an hourly wage of 10 EUR. Participants were fluent in German, healthy, and were not taking any medication that might affect affective functioning (e.g., antidepressants). Some 53.1 % ($n = 26$) of the participants were female. The mean age of the participants was 24.8 ($SD = 3.5$). Three sets of stimuli were used in three discrete choice experiments (Louviere & Woodworth, 1983) to increase the generalizability of the results: charity options, face options, and yogurt options. All three stimuli types were described by three attributes with two levels each (see Table 5).

Table 5 - Attributes and attribute levels for charity, face, and yogurt stimuli.

	Stimulus 1: Charity options	Attribute levels	
Attributes	Living conditions	Bad	Moderate
	Family size	6 people	3 people
	Willingness to learn	Low	Average
	Stimulus 2: Face options	Attribute levels	
Attributes	Eyes	Small	Big
	Nose	Small	Big
	Mouth	Small	Big
	Stimulus 3: Yogurt options	Attribute levels	
Attributes	Fat content	1.5%	3.5%
	Taste	Apricot	Strawberry
	Label	Best standard	Organic

The full-factorial combination of attributes and attribute levels produces a 2 x 2 x 2 factorial, or eight option descriptions per stimulus-type. These eight alternatives were assigned to 12 choice sets, each with two options. The choice set design is orthogonal and balanced, as suggested by Street and Burgess (2004); see Table 6 for an overview of the choice set design.

Table 6 - Effects-coded, balanced, and orthogonal design of choice options (charity / faces / yogurts) in 12 choice sets.

	Option 1			Option 2		
Charity	Living conditions	Family size	Willingness to learn	Living conditions	Family size	Willingness to learn
Faces	Eyes	Nose	Mouth	Eyes	Nose	Mouth
Yogurt	Taste	Fat content	Label	Taste	Fat content	Label
Choice set						
1	-1	-1	-1	-1	1	1
2	-1	-1	1	-1	1	-1
3	1	-1	-1	1	1	1
4	1	-1	1	1	1	-1
5	-1	-1	-1	1	-1	1
6	1	-1	-1	-1	-1	1
7	-1	1	-1	1	1	1
8	1	1	-1	-1	1	1
9	-1	-1	-1	1	1	-1
10	1	1	1	-1	-1	1
11	-1	1	-1	1	-1	-1
12	1	-1	1	-1	1	1

For charity options, living condition is coded 1 for bad, and -1 for moderate; family size is coded 1 for 6 people, and -1 for 3 people; and willingness to learn is coded 1 for low, and -1 for average. For face options, eyes, nose and mouth are coded 1 for big, and -1 for small. Yogurt taste is coded 1 for strawberry, and -1 for apricot. Yogurt fat content is coded 1 for 3.5%, and -1 for 1.5%. Yogurt label is coded 1 for organic, and -1 for best standard. Figure 7 illustrates the attribute levels of all three stimuli in use.

Figure 7 - Example choice sets for charity, face, and yogurt decisions (see Appendix D for full set of options)[4].

[4] Options on the left side have attribute levels with the coding 1, 1, -1, and the opposite coding on the right side (-1, -1, 1).

Participants were asked for certain exclusion criteria that could disturb the measurement of fEMG (particular medications, alcohol, nicotine abuse, caffeine abuse, etc., were not allowed), and demographic questions. Participants were asked to sit in a comfortable chair in an attenuated and dimly lit room. Instructions and stimuli were presented on a 17’’ monitor placed approximately 70 cm in front of the participants. fEMG surface-electrodes were attached on the left side of each subject’s face (Rinn, 1984).

Following the setup, the experimental procedure lasted approximately 50 minutes. A computer program presented instructions and choice sets to the participants (Presentation, Neurobs Inc.). Synchronized event markers were used to align fEMG data and behavioral choices (indicated by the press of a button). Participants received a short instruction that included practice on how to use the choice buttons, the stimulus presentation, and the attributes and attribute levels of each stimulus type. A 2-second fixation-cross was presented for the alignment of initial visual attention and baseline-correction of fEMG measures. Choice sets were presented without a time limit, with each presentation ending by choice (button press). After each choice, respondents received a 10-second rest period to regain an affective baseline, and then they progressed at their own pace. Figure 8 shows the course of action in a choice set.

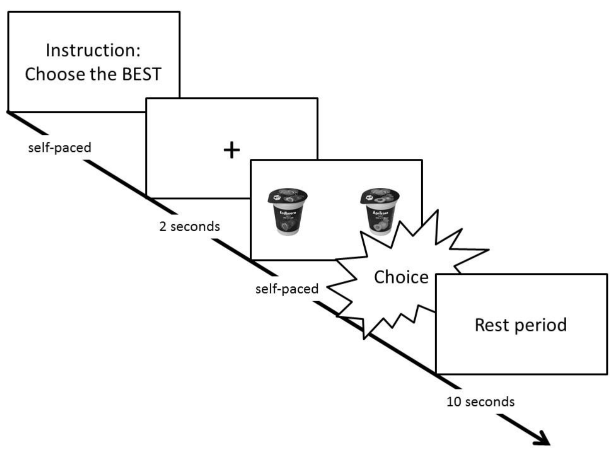


Figure 8 - Course of a choice set with fEMG measurement.

The presentation of the three discrete choice experiments started with face options, were followed by the charity options, and ended with the yogurt options. Between the three DCEs control questions and stimulus-conform holdout tasks were presented (four options that had to be ranked by preference). During the DCEs, immediate affect was measured with facial electromyography.

4.7.1.1 Measurement of immediate affect with fEMG

The measurement of immediate affect via facial electromyography is an established method and has proved reliable in various task contexts (e.g., J. T. Larsen et al., 2003). The use of corrugator supercilii (frown muscle) and zygomaticus major (smile muscle) to study affect has its origins in the pioneering research by Schwartz, Brown, and Ahern (1980), who found that unpleasant imagery elicited greater activity in the frown muscle than pleasant imagery, whereas pleasant imagery elicited greater activity in the smile muscle. Schwartz's imagery tasks generalize to a multiplicity of affective tasks. For example, Cacioppo and Petty (1979) reported that counter-attitudinal persuasive messages elicited greater activity in frown muscle and less activity in smile muscle than pro-attitudinal and neutral messages. Similarly, pictures of unpleasant scenes (Cacioppo, Petty, Losch, & Kim, 1986; Lang, Greenwald, Bradley, & Hamm, 1993) and faces (Dimberg, Thunberg, & Elmehed, 2000) elicit more activity in the frown muscle than do pleasant scenes and faces, but less activity in the smile muscle (for a review see Tassinary & Cacioppo, 2000). These simple bipolar and linear interpretations of facial EMG measures do not hold in extreme affective settings (J. T. Larsen et al., 2003), but this is not expected in a consumer DCE context.

Facial EMG was recorded bipolarly (for common-mode rejection, i.e., rejection of interfering muscle signals) over corrugator supercilii (frown muscle) and zygomaticus major (smile muscle) on the left side of the face with 4-mm standard silver/silver-chloride electrodes. An implicit reference electrode and a ground electrode were placed in the middle of the forehead below the hairline, as no muscle activity is expected at that position (see Figure 9).

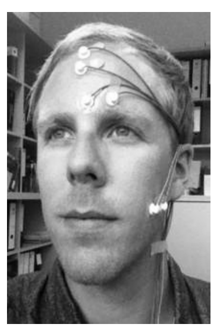


Figure 9 - Placement of fEMG electrodes over the frown muscle (corrugator supercilii), and the smile muscle (zygomaticus major), and ground and reference electrodes in the middle of the forehead, below the hairline.

The fEMG electrode sites were abraded with abrasive paste and isopropyl alcohol pads prior to electrode placement. fEMG signals were relayed through a cable to the V-AMP amplifier (BrainProducts), where signals were amplified. The signals were digitized at 2000 Hz and then saved and presented on a laboratory computer. The experimenter inspected incoming fEMG data to monitor artifacts (measurement errors, e.g., due to movement). Offline, data was submitted to a 20 Hz high-pass filter, a 500 Hz low-pass filter, and a 50 Hz notch-filter (van Boxtel, 2010) to reduce movement artifacts and power supply system artifacts, then fully rectified. Data with remaining artifacts were excluded from subsequent analyses. Overall, the procedure was conducted according to the guidelines for human electromyographic research published by Fridlund and Cacioppo (1986). Figure 10 depicts the filtered fEMG signal of the smile muscle with an expression of positive valence.

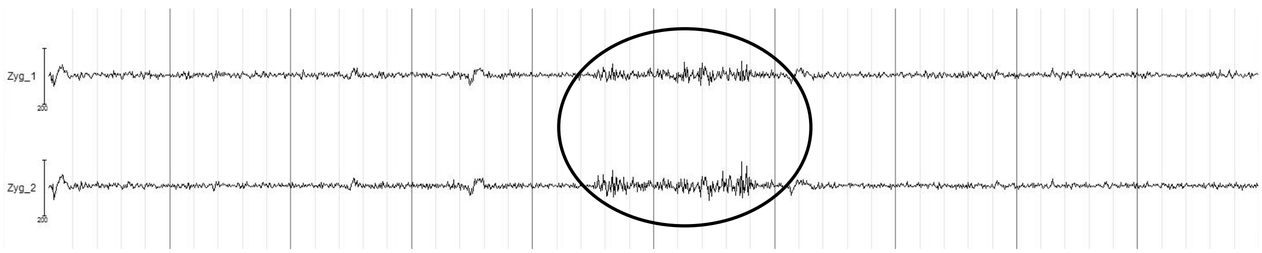


Figure 10 - Filtered fEMG signals from smile muscle with an expression of positive valence.

Following Tassinary and Cacioppo (2000), fEMG activity was measured as the difference between activity during the stimulus presentation, and the 1,000 ms immediately before stimulus presentation (fixation cross-presentation). Baseline-corrected fEMG peak values were used for further analysis due to varying decision durations. The fEMG data were log-transformed prior to statistical (regression) analysis (see Appendix B for details of fEMG measurement and analysis).

4.7.1.2 Data

In total, 588 choices from 49 participants (49 participants x 12 choices) were observed in each stimulus type (charity, faces, yogurts). An overview about the muscle activity across choice sets in each stimulus type shows no distinct habituation effects across the 12 choice sets per stimulus type (see Figure 11).

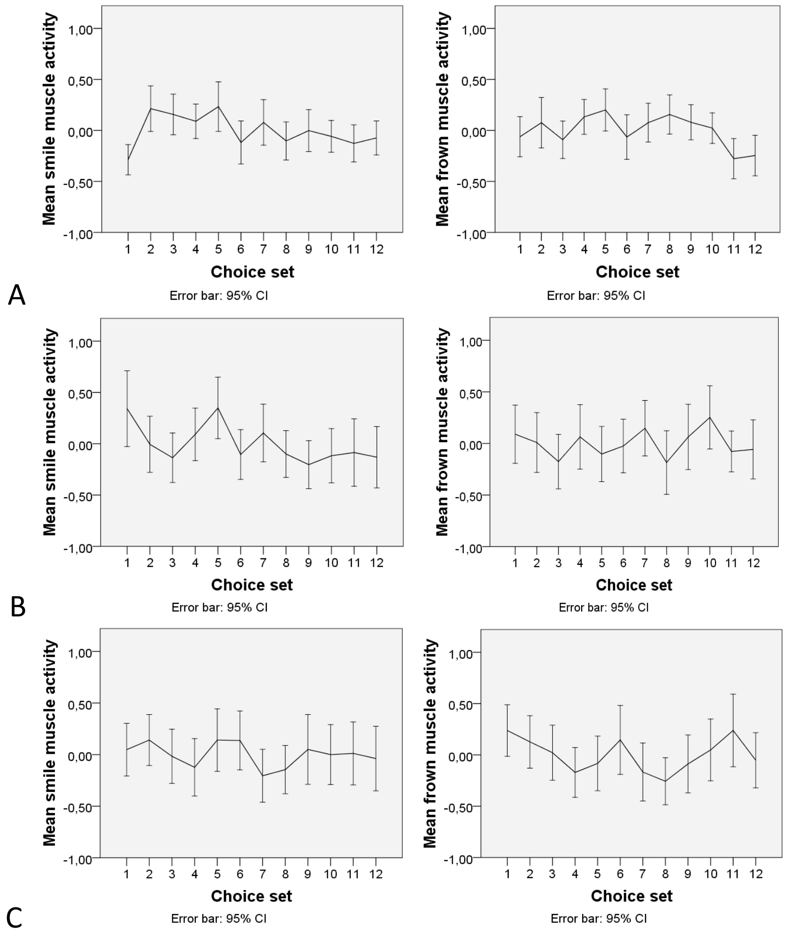


Figure 11 - Facial muscle activity across all 12 choice sets per stimulus material (A = charity; B = faces; C = yogurts).

Correlation between frown and smile muscle activity indicates that there is some overlap (around 23%) but also enough distinct variance between positive and negative valence for a substantiated contribution (see Table 7). This moderate correlation also implies that there could be a simultaneous activation of frown and smile muscle activity that would indicate ambivalence.

Table 7 - Correlation of frown muscle and smile muscle activity.

Correlation	r (df =586)	p-value
Charity: Smile - frown	.208	<.001
Faces: Smile - frown	.261	<.001
Yogurts: Smile - frown	.221	<.001

Ambivalence and indifference as extremes of the combined observation of the smile and the frown muscle is calculated as the sum of the smile and frown muscle activity in a compensatory fashion. As high smile muscle activity indicates positive affect, and high frown muscle activity indicates negative affect, ambivalence is indicated when both muscles show high activity, and indifference is indicated when both muscles show low activity. No ambivalence and indifference is indicated when either the smile muscle, or the frown muscle shows high activity, or both muscles show moderate activity. Thus, the sums of the two affect-indicating facial muscles are divided in quartiles based on individual-related measures, in which the first and the fourth quartile indicate low and high activity of both muscles (indifference / ambivalence). The second and third quartiles indicate moderate activity of both muscles, or activity of either frown or smile muscle (no indifference nor ambivalence). The correlations of smile and frown muscle activity with the ambivalence values indicate high overlaps between these values (see Table 8), which is not surprising, as these values constitute the ambivalence value. Especially the smile muscle activity contributes to the ambivalence values.

Table 8 - Correlation of frown and smile activity with ambivalence (ambi.) / indifference (indiff.) values.

Correlation	r (df = 586)	p-value
Charity		
Smile - ambi. / indiff.	.908	<.001
Frown - ambi. / indiff.	.534	<.001
Faces		
Smile - ambi. / indiff.	.873	<.001
Frown - ambi. / indiff.	.616	<.001
Yogurts		
Smile - ambi. / indiff.	.872	<.001
Frown - ambi. / indiff.	.594	<.001

4.7.2 Results

For hypothesis testing, choice samples are split in half, based on the median of the fEMG values. The result is a high and low smile activity choice sample, a high and low frown activity choice sample, and a high and low ambivalence / indifference choice sample. As these samples have the same number of observations (588 / 2 = 294; median split), and the same number of parameters (6), the likelihood ratio test suggested by Swait and Louviere (1993) can be used to compare choice models with either high or low accompanying fEMG values.

The splitting of the choice sample could result in an unbalanced experimental design, and therefore the balance was tested. Results suggest that only the negative affect choice samples in face choices and the ambivalence choice samples in yogurt choices significantly differ in the number of choice sets to be judged (see Table 9).

Table 9 - Check of balance (comparable frequencies of choice sets) in split samples of choices based on fEMG values.

Split samples of choices	Chi-square value (df)	P-value
Charity decisions		
Smile activity high vs. low	13.63 (11)	.254
Frown activity high vs. low	14.61 (11)	.201
Arousal high vs. low	12.98 (11)	.295
Ambiv. / indiff. high vs. low	17.71 (11)	.088
Face decisions		
Smile activity high vs. low	10.52 (11)	.484
Frown activity high vs. low	10.20 (11)	.512
Arousal high vs. low	15.59 (11)	.157
Ambi. / indiff. high vs. low	**20.00 (11)**	**.045**
Yogurt decisions		
Smile activity high vs. low	7.42 (11)	.763
Frown activity high vs. low	**20.16 (11)**	**.043**
Arousal high vs. low	10.69 (11)	.469
Ambi. / indiff. high vs. low	10.53 (11)	.483

Conditional logit models (e.g., Train, 2009) based on behavioral choice, as well as choices with either high or low smile muscle or frown muscle activity, or high and low ambivalence, are compared with each other in order to examine the hypothesis. Here, it is important to note that smile muscle and frown muscle activity can indicate positive and negative affect (J. T. Larsen et al., 2003). The holdout prediction as predictive validity indicator correlates predicted ranks, based on model estimates, with empirically derived preference ranks in a holdout task.

For charity decisions, results indicate that the splitting of choices based on smile and frown muscle activity improves variance explanation compared with the baseline model. This is indicated by the significant likelihood ratio tests presented in Table 10. The BIC further indicates that there is a meaningful difference between choice models with high and low muscle activity, based on either smile or frown muscle activity (Kass & Raftery, 1995, suggest that differences in BIC higher than two points can be considered meaningful). For choice models based on smile muscle activity, the negative affect model indicates higher internal validity (based on BIC). For choice models based on frown muscle activity, the negative affect model indicates higher internal validity (based on BIC). Yet, both negative affect models cannot outperform the behavioral choice model in terms of predictive validity, thus H2.1 (somatic markers) can only be confirmed for internal validity but not for predictive validity. Interestingly, the best fitting models based on affect are the negative affect models based on frown and smile muscle activity. For charity decisions, positive affect seems to result in less internal (conforming to the hypothesis) and less predictive validity (not conforming to the hypothesis) regarding preference analysis, thus H2.2 (information processing) cannot be confirmed for charity decisions.

Table 10 – Choice models with positive and negative affective valence in charity decisions.

	Behavioral choice		Smile – positive affect		Smile – negative affect		Frown – negative affect		Frown – positive affect	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Living cond. – bad	**1.33*** **	0.11	**1.37*** **	0.16	**1.42*** **	0.17	**1.73*** **	0.41	**1.23*** **	0.14
Living cond. – moderate	**-1.33*** **		**-1.37*** **		**-1.42*** **		**-1.73*** **		**-1.23*** **	
Family size – 3	**-0.40*** **	0.09	**-0.43** **	0.15	**-0.44** **	0.16	-0.79+	0.41	**-0.29***	0.12
Family size – 6	**0.40*** **		**0.43** **		**0.44** **		0.79+		**0.29***	
Will. learn – avg.	**-0.96*** **	0.09	**-0.95*** **	0.15	**-1.10*** **	0.17	**-1.38*** **	0.41	**-0.84*** **	0.12
Will. learn – low	**0.96*** **		**0.95*** **		**1.10*** **		**1.38*** **		**0.84*** **	
Living X Family – diff.	0.15	0.09	**0.34***	0.15	-0.06	0.17	0.46	0.41	0.13	0.12
Living X Family – same	-0.15		**-0,34***		0.06		-0.46		-0.13	
Living X Learn – diff.	-0.01	0.09	0.05	0.15	-0.09	0.16	0.41	0.40	-0.15	0.12
Living X Learn – same	0.01		-0.05		0.09		-0.41		0.15	
Family X Learn – diff.	-0.01	0.10	-0.31+	0.17	0.31+	0.17	-0.32	0.41	-0.01	0.14
Family X Learn – same	0.01		0.31+		-0.31+		0.32		0.01	
Statistics										
Nobs	588		294		294		294		294	
No. of parameters	6		6		6		6		6	
LN likelihood	-195.35		-103.40		-86.91		-90.03		-101.37	
LR test	Crit. χ^2 (α=.05; df=1) = 3.84		10.07				7.87			
BIC	414.05		230.15		197.16		203.42		226.10	
Adj. pseudo-R^2(0)	0.60		0.57		0.64		0.62		0.58	
Holdout prediction	0.75		0.75		0.75		0.75		0.73	

(*** = p < .001; ** = p < .01; * = p < .05; + = p < .10)

For preference decisions related to faces, results show another picture (see Table 11). Again, the likelihood ratio test suggests that the splitting of the behavioral model based on the facial muscle activity measures can explain more variance than the behavioral model alone. Contrary to charity decisions, the internal validity of positive affect models outperforms those of the negative affect models (all BIC differences > 2, see Kass & Raftery, 1995). Yet, predictive validity measures (holdout prediction) favor choice models based on negative affect. Independent of positive and negative affect models, internal and predictive validity improve by the incorporation of affect. Thus, these results support hypothesis 2.1 (somatic markers). Contrary to what was expected, estimated choice models do not show lower (higher) internal validity for positive (negative) affect, and higher (lower) predictive validity for positive (negative) affect. Thus, the results relating to face preference decisions cannot confirm H2.2 (information-processing).

Table 11 – Choice models with positive and negative affective valence in face decisions.

	Behavioral choice		Smile – positive affect		Smile – negative affect		Frown – negative affect		Frown – positive affect	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Eyes – small	**-0.34*** **	0.05	**-0.42*** **	0.08	**-0.27*** **	0.07	**-0.34*** **	0.08	**-0.29*** **	0.08
Eyes – big	**0.34*** **		**0.42*** **		**0.27*** **		**0.34*** **		**0.29*** **	
Nose – small	**0.23*** **	0.05	**0.16* **	0.07	**0.32*** **	0.08	**0.16* **	0.07	**0.32*** **	0.08
Nose – big	**-0.23*** **		**-0.16* **		**-0.32*** **		**-0.16* **		**-0.32*** **	
Mouth – small	-0.04	0.05	-0.07	0.07	-0.02	0.07	-0.08	0.07	0.01	0.08
Mouth – big	0.04		0.07		0.02		0.08		-0.01	
Eyes X Nose – diff	**-0.16** **	0.05	-0.12	0.07	**-0.19** **	0.07	-0.04	0.07	**-0.29*** **	0.08
Eyes X Nose – same	**0.16** **		0.12		**0.19** **		0.04		**0.29*** **	
Eyes X Mouth – diff.	**-0.15** **	0.05	**-0.17* **	0.07	-0.11	0.08	-0.07	0.08	**-0.22** **	0.08
Eyes X Mouth – same	**0.15** **		**0.17* **		0.11		0.07		**0.22** **	
Nose X Mouth – diff.	**0.20*** **	0.05	**0.16* **	0.08	**0.23** **	0.07	**0.19* **	0.08	**0.21** **	0.08
Nose X Mouth – same	**-0.20*** **		**-0.16* **		**-0.23** **		**-0.19* **		**-0.21** **	
Statistics										
Nobs	588		293		295		294		294	
No. of parameters	6		6		6		6		6	
LN likelihood	-365.51		-180.40		-182.10		-185.33		-175.12	
LR test	Crit. χ^2 (α=.05; df=1) = 3.84		6.01				10.11			
BIC	754.37		384.15		387.56		394.01		373.59	
Adj. pseudo-R^2(0)	0.13		0.15		0.14		0.12		0.17	
Holdout prediction	-0.03		-0.03		0.06		-0.03		0.03	

(*** = p < .001; ** = p < .01; * = p < .05)

The likelihood ratio tests suggest that splitting of the behavioral choices for yogurt decisions based on frown and smile muscle activity explains more variance than the behavioral model alone. Comparable to results for charity decisions, and contrary to results for face decisions, BIC values based on negative affect (inferred from either smile or frown muscle) differ meaningfully from the behavioral and positive affect models (see Kass & Rafterty, 1995) and indicate higher internal validity (see Table 12). In matters of predictive validity, the smile muscle shows meaningful differences between positive and negative affect, but cannot outperform the behavioral choice model. Thus, H2.1 (somatic marker) can only be confirmed for internal validity but not for predictive validity.

As the negative affect models based on smile muscle activity show higher internal validity and lower predictive validity compared with the smile-based positive affect model, H2.2 (information-processing) can be partly confirmed. For a full confirmation, the negative affect model based on frown activity should have led to a lower predictive validity compared with the frown-based positive affect choice model, which is not the case.

Table 12 – Choice models with positive and negative affective valence in yogurt decisions.

	Behavioral choice		Smile –positive affect		Smile – negative affect		Frown – negative affect		Frown – positive affect	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Taste – apricot	**-0.17*** **	0.05	**-0.16***	0.07	**-0.17***	0.08	**-0.22** **	0.08	-0.12+	0.07
Taste – strawberry	**0.17*** **		**0.16***		**0.17***		**0.22** **		0.12+	
Fat content – 1.5%	0.03	0.05	-0.04	0.07	0.12	0.08	0.04	0.07	0.04	0.07
Fat content – 3.5%	-0.03		0.04		-0.12		-0.04		-0.04	
Label – best standard	**-0.47*** **	0.06	**-0.43*** **	0.08	**-0.53*** **	0.08	**-0.56*** **	0.08	**-0.38*** **	0.08
Label – organic	**0.47*** **		**0.43*** **		**0.53*** **		**0.56*** **		**0.38*** **	
Taste X Fat content – diff.	-0.04	0.06	0.08	0.08	**-0.19***	0.08	-0.02	0.08	-0.07	0.08
Taste X Fat content – same	0.04		-0.08		**0.19***		0.02		0.07	
Taste X Label – diff.	-0.01	0.05	0.09	0.07	-0.11	0.08	-0.01	0.07	-0.03	0.08
Taste X Label – same	0.01		-0.09		0.11		0.01		0.03	
Fat content X Label – diff.	0.02	0.05	0.06	0.07	-0.02	0.07	-0.05	0.08	0.07	0.07
Fat content X Label – same	-0.02		-0.06		0.02		0.05		-0.07	
Statistics										
Nobs	588		294		294		294		294	
No. of parameters	6		6		6		6		6	
LN-Likelihood	-363.65		-182.63		-174.52		-172.89		-188.08	
LR-test	Crit. χ^2 (α=.05; df=1) = 3.84		12.97				5.34			
BIC	750.65		388.62		372.40		369.14		399.51	
Adj. pseudo-R^2(0)	0.14		0.14		0.19		0.19		0.10	
Holdout prediction	0.53		0.53		0.45		0.53		0.53	

(*** = p < .001; ** = p < .01; * = p < .05; + = p < .10)

An analysis for two of three stimulus types allows the confirmation of the somatic marker hypothesis (H2.1), but the information-processing hypothesis (H2.2) is only partly confirmed in preference decisions for yogurts.

The ambivalence / indifference values of choices for charity decision do not seem to be a meaningful factor to split the behavioral choice sample, as indicated by the likelihood ratio test (see Table 13). Yet, the BIC measures indicate that the choice sample with low ambivalence / indifference provides a better model fit than the choices with high ambivalence / indifference. Predictive validity does not change across the behavioral and the two ambivalence / indifference models. Thus, hypothesis 2.3 cannot be confirmed, although the model fits of the ambivalence / indifference models alone point in the right direction.

Table 13 – Choice models with higher and lower experienced ambivalence / indifference in charity decisions.

	Behavioral choice		High ambivalence / indifference		Low ambivalence / indifference	
	Par.	SE	Par.	SE	Par.	SE
Living cond. – bad	**1.33*****	0.11	**1.22*****	0.13	**1.48*****	0.12
Living cond. – moderate	**-1.33*****		**-1.22*****		**-1.48*****	
Family size – 3	**-0.40*****	0.09	**-0.36****	0.12	**-0.48****	0.12
Family size – 6	**0.40*****		**0.36****		**0.48****	
Will. learn – avg.	**-0.96*****	0.09	**-0.88*****	0.12	**-1.05*****	0.13
Will. learn – low	**0.96*****		**0.88*****		**1.05*****	
Living X Family – diff.	0.15	0.09	0.13	0.12	0.18	0.13
Living X Family – same	-0.15		-0.13		-0.18	
Living X Learn – diff.	-0.01	0.09	0.01	0.12	0.01	0.12
Living X Learn – same	0.01		-0.01		-0.01	
Family X Learn – diff.	-0.01	0.10	0.06	0.14	-0.12	0.13
Family X Learn – same	0.01		-0.06		0.12	
Statistics						
Nobs	588		294		294	
No. of parameters	6		6		6	
LN likelihood	-195.35		-104.84		-89.25	
LR test	Crit. χ^2 (α=.05; df=1) = 3.84		2.50			
BIC	414.05		233.03		201.86	
Adj. pseudo-R2(0)	0.60		0.56		0.64	
Holdout prediction	0.75		0.75		0.75	

(*** = p < .001; ** = p < .01; * = p < .05)

Relating to face decisions, the likelihood ratio test indicates that in this sample, the splitting based on the ambivalence / indifference values does explain incremental variance compared with the behavioral model (see Table 14). The BIC measures further indicate that the low ambivalence / indifference model outperforms the high ambivalence / indifference model with regard to internal validity. Predictive validity indicates that the low ambivalence / indifference model performs badly, but also that the high ambivalence / indifference model does even worse. Owing to the meaningless predictive validity of the low ambivalence / indifference model (r=0.01), hypothesis 2.3 can only be partially confirmed for face decisions.

Table 14 – Choice models with higher and lower experienced ambivalence / indifference in face decisions.

	Behavioral choice		High ambivalence / indifference		Low ambivalence / indifference	
	Par.	SE	Par.	SE	Par.	SE
Eyes – small	**-0.34*** **	0.05	**-0.33*** **	0.08	**-0.37*** **	0.08
Eyes – big	**0.34*** **		**0.33*** **		**0.37*** **	
Nose – small	**0.23*** **	0.05	**0.21** **	0.08	**0.23** **	0.07
Nose – big	**-0.23*** **		**-0.21** **		**-0.23** **	
Mouth – small	-0.04	0.05	-0.09	0.07	-0.01	0.08
Mouth – big	0.04		0.09		0.01	
Eyes X Nose – diff	**-0.16** **	0.05	**-0.19***	0.07	-0.14+	0.08
Eyes X Nose – same	**0.16** **		**0.19***		0.14+	
Eyes X Mouth – diff-	**-0.15** **	0.05	**-0.22** **	0.08	-0.08	0.07
Eyes X Mouth – same	**0.15** **		**0.22** **		0.08	
Nose X Mouth – diff.	**0.20*** **	0.05	0.12	0.08	**0.27*** **	0.08
Nose X Mouth – same	**-0.20*** **		-0.12		**-0.27** **	
Statistics						
Nobs	588		294		294	
No. of parameters	6		6		6	
LN likelihood	-365.51		-183.27		-179.97	
LR test	Crit. χ^2 (α=.05; df=1) = 3.84		4.53			
BIC	754.37		389.89		383.29	
Adj. pseudo-R2(0)	0.13		0.13		0.15	
Holdout prediction	-0.03		-0.06		0.01	

(*** = p < .001; ** = p < .01; * = p < .05; + = p < .10)

For yogurt decisions, neither the likelihood ratio test, nor the BIC, nor the holdout prediction, indicates that ambivalence / indifference values make sense as a splitting factor for the behavioral choices (see Table 15). BIC values only differ marginal between high and low ambivalence / indifference models, and holdout prediction does not differ between all three choice models. Thus, for yogurt decisions, hypothesis 2.3 cannot be confirmed.

Table 15 – Choice models with higher and lower experienced ambivalence / indifference in yogurt decisions.

	Behavioral choice		High ambivalence / indifference		Low ambivalence / indifference	
	Par.	SE	Par.	SE	Par.	SE
Taste – apricot	**-0.17*** **	0.05	**-0.18***	0.07	**-0.15***	0.07
Taste – strawberry	**0.17*** **		**0.18***		**0.15***	
Fat content – 1.5%	0.03	0.05	0.01	0.07	0.07	0.07
Fat content – 3.5%	-0.03		-0.01		-0.07	
Label – best standard	**-0.47*** **	0.06	**-0.47*** **	0.08	**-0.45*** **	0.08
Label – organic	**0.47*** **		**0.47*** **		**0.45*** **	
Taste X Fat content – diff.	-0.04	0.06	-0.02	0.08	-0.05	0.08
Taste X Fat content – same	0.04		0.02		0.05	
Taste X Label – diff.	-0.01	0.05	-0.01	0.07	-0.02	0.07
Taste X Label – same	0.01		0.01		0.02	
Fat content X Label – diff.	0.02	0.05	0.08	0.07	-0.05	0.07
Fat content X Label – same	-0.02		-0.08		0.05	
Statistics						
Nobs	588		294		294	
No. of parameters	6		6		6	
LN likelihood	-363.65		-180.84		-181.64	
LR test	Crit. χ^2 (α=.05; df=1) = 3.84		2.31			
BIC	750.65		385.04		386.63	
Adj. pseudo-R2(0)	0.14		0.14		0.14	
Holdout prediction	0.53		0.53		0.53	

(*** = p < .001; ** = p < .01; * = p < .05)

4.7.3 Discussion

The splitting of behavioral choice samples in choice with high and low affect based on fEMG measures allows a closer look at the role of immediate affect during consumer decision-making in a discrete choice context. Overall, results suggest that information that is implicitly transported by affect during consumer choice is actively used for evaluation and preference construction (in line with Peters, 2006, for example). Thus, pleasure and pain that accompany preference decisions can be seen as an additional source of utility that informs the decision-maker, sometime erroneously, about the expected utility of a consequence (e.g., Mellers, 2000).

Two of three analysis results support the role of affect as a somatic marker. In relation to charity and yogurt decisions, results for internal validity support the somatic marker hypothesis, yet no model based on (positive or negative) affect could outperform the behavioral baseline model for predictive validity. One reason for this partial refutation might be the more rational task demand in charity and yogurt decisions compared with face decisions. A more systematic decision process probably led to a ceiling effect related to holdout performance in charity and yogurt decisions (charity holdout = 75%, and yogurt holdout = 53%). This assumption is underpinned by a post hoc analysis of control variables that measures the holistic vs. analytic perception of stimuli on a subjective level (four items with a Cronbach's alpha of .705, in which 1 means analytic, and 5 means holistic, see Appendix A for details). Here, charity options ($M = 1.9$) and yogurt options ($M = 2.0$) were perceived to be significantly more analytic, compared with face options ($M = 2.8$; charity vs. faces: $t(48) = 4.8$; $p < .001$; yogurt vs. faces: $t(48) = 4.36$; $p < .001$; charity vs. yogurts: $t(48) = -0.93$; $p = .356$).

Preference decisions for faces fully support the somatic marker hypotheses (H2.1). Results suggest that choices with either a more positive or negative affect show higher internal validity, and also higher predictive validity. The overall low predictive validity improved from a meaningless level ($r = -.03$) to an at least minimally meaningful level through a consideration of immediate affect ($r = .06$; Cohen, 1992). The relatively artificial stimulus presentation (affectively neutral faces with no hair) might have led to this overall low behavioral predictive validity, which shows the chance of measuring affect in consumer decision-making. Reason-based unfamiliarity might be compensated for by reliance on affective information that is marked to more or less distant associations with the choice options (in line with Damasio, 1994).

The hypothesis that deals with the influence of affect on information processing (H2.2) is only partly corroborated by smile muscle activity in yogurt decisions. For face decisions, results are even counter to expectations; here, negative affect based on the smile muscle leads to less internal and higher predictive validity, compared with the model based on positive affect indicated by the smile muscle.

The rational task demand of the charity decisions (tabular textual stimuli), and the artificiality of the face options (neutral hairless faces), might have distorted natural information processing. In respect of charity options, information processing might have been very systematic (see overall high internal and predictive validity), so affect could not have influenced this strategy.

By contrast, affect might not have had a chance to interact with information processing in face decisions, as information processing could have been very heuristic (see overall low internal and predictive validity). Interestingly, the best-fitting choice models for charity decision are negative affect models (based on smile and frown muscle activity), and for face decisions the best-fitting choice models are positive affect models (based on smile and frown muscle activity). The previous assumptions are supported by the best-fitting choice models in charity and face decisions, as negative affect is associated with systematic processing, and positive affect is associated with heuristic processing (e.g., Schwarz & Clore, 1996).

In the case of yogurts, task demand (pictorial and textual attribute levels) could have matched with natural decision-making and thus affected mediated information processing. Here, negative affect led to high internal validity due to systematic processing, and to low predictive validity due to the lack of reliance on pre-existing knowledge (e.g., Loewenstein & Lerner, 2003).

Ambivalence and indifference as the two extremes of common positive and negative affective reaction do not seem to play a relevant role for the preference analysis for two of the three stimuli types. For face decisions, there is meaningful improvement of preference analysis related to internal validity for choices with low ambivalence / indifference. Although ambivalence / indifference cannot be considered a meaningful factor in charity decisions, the internal validity at least indicates that choices with low ambivalence / indifference outperform choices with high ambivalence / indifference.

As the overall higher internal and predictive validity of charity and yogurt decisions indicate the presumably higher certainty of decision-making (compared with face decisions), there just might have been no need to feel ambivalent or indifferent in these cases. Again, the artificiality of the face stimuli might have induced ambivalence / indifference, whereas charity and yogurt options were considered clearly distinguishable. As the difference between the attribute levels of faces was subtle (small and big eyes, nose, and mouth), the difference between attribute levels of charity and yogurt options was clear-cut. It is therefore coherent that clearly identifiable differences in charity and yogurt options did not induce a feeling of ambivalence, as one option could be clearly identified as liked / disliked. These assumptions are underpinned by a post hoc analysis of the subjective difficulty of decision-making for all three stimuli types (subjective difficulty was measured with four items that have a Cronbach's alpha of .776, in which 1 means "difficult", and 5 means "easy", see Appendix A for details). Here, faces were perceived as most difficult ($M = 2.9$), followed by charity options ($M = 3.2$, difference to faces $t(48) = -1.8$; $p = .07$), and easiest decisions were made for yogurts ($M = 4.2$, difference to faces: $t(48) = -7.7$; $p < .001$).

Thus, the idea of a two dimensional positive and negative affective experience (Cacioppo & Berntson, 1994) cannot be discarded on the basis of these results. If the task (stimulus) induces ambivalence / indifference, the measurement of ambivalence could indicate a process of preference construction, which is likely to happen in highly ambivalent / indifferent decision situations (Nowlis, Kahn, & Dhar, 2002).

4.8 Summary and outlook of affective valence in consumer decision-making

On the whole, immediate affective valence during preference decisions in DCEs most probably has an important information function (as suggested by Peters, 2006). Depending on the induced task demand, affect can have further indicative functions. Results suggest that the effects of information processing and ambivalence / indifference during preference decisions are reflected in immediate affect.

In relation to preference construction, findings indicate that choices with higher affect (positive or negative) might result in more stable preference expression, as there are somatic affective markers that guide decision-making (Bechara, 2004). Furthermore, positive and negative affect might have a differential impact on the modality of constructive processes, due to information processing. Negative affect could be accompanied by systematic processing, which led to preference construction in a longer term, whereas positive affect led to immediate construction. Trivially, affectively indicated ambivalence or indifference probably leads to preference construction.

Thus, measurement of affect in DCEs leads to a valuable additional insight for the investigation of preference decision-making and the prediction of choice. Especially for the prediction of choice, the additional consideration of immediate affect could yield practically relevant benefits. The best-fitting choice models with immediate affect for charity, face, and yogurt options suggest significantly differing optimal products based on the parameter estimates (see tables 13, 14, and 15) compared with the respective behavioral model. With regard to ambivalence / indifference, as a result of differing parameter estimates in relation to the purely behavioral model, there is incremental insight if this factor makes sense, in face decisions. This very clearly suggests that the additional integration of affect at least allows for a differentiated look at preferences. It is presumed that immediate affect is guiding behavior, especially in situations in which automatic "lower-order" processes takes over control in decisions, f.ex., related to fast-moving consumer goods, or in situations with time pressure (e.g., Shiv & Fedorikhin, 1999). Thus, the additional integration of immediate affect could yield a more valid picture of what is actually happening when consumers make decisions in real-world circumstances.

Limiting factors for the practical relevance of the findings are the differences in holdout prediction of valence-based choice models, which are rather low. The differences range from zero to 0.09, whereas a level of 0.1 would indicate meaningfulness (see Cohen, 1992). The response mode of the holdout prediction task (ranking) differed from the response mode of the preference elicitation task (choices). The variation of response mode could be one reason for the overall low differences regarding holdout prediction of complementing arousal-related choice models. Changes in response mode can already lead to preference construction (Payne et al., 1999a; Schkade & Johnson, 1989), which possibly masked effects concerned with arousal. In order to control for effects of response mode, future research should use the same response mode in the holdout prediction task and in the preference elicitation task. A further control of probable effects of affective valence on preference construction in the holdout task would complete a sound testing of predictive validity.

The approach taken in this study certainly provided evidence for the feasibility of measuring fEMG during consumer choice, as well as for the splitting of choice models based on these measures. Owing to the results for three different stimulus types, it is suggested to measure both muscles (smile and frown) in order to infer negative and positive immediate affect. Presumably, depending on the task demand that is induced by the stimulus type, either the frown muscle or the smile muscle is better at indicating positive of negative valence. In this study, choice models generated on the frown muscle data discriminated better than choice models based on smile muscle data in charity options, likely because of induced seriousness. By contrast, for yogurt decisions, choice models based on the smile muscle discriminated better than choice models based on the frown muscle data, likely because of an inherent hedonic tendency toward yogurts.

A limiting alternative interpretation of corrugator activity is that frown activity indicates mental effort. Veldhuizen, Gaillard, and de Vries (2003) found an interrelation between frown activity and mental fatigue, which is associated with boredom and exhaustion. As mental fatigue builds up during a day, this alternative interpretation of frown muscle activity is not plausible in this study. Yet, studies that manipulated task difficulty (van Boxtel & Jessurun, 1993; Waterink & van Boxtel, 1994) - even physical task difficulty (de Morree & Marcora, 2010) - found an association between higher task demands and more corrugator activity. Although a recent study did not find this association (Capa, Audiffren, & Ragot, 2008), the alternative meaning of corrugator activity should be considered a possibly limiting factor of fEMG measures.

The splitting of choice models based on the fEMG measures worked out well, as the number of attribute levels that were presented mostly did not significantly differ between the divided models. Yet, this does not have to be the case, as shown for the ambivalence / indifference split for faces and the frown muscle split for yogurts. In these cases, a difference between choice models based on affect cannot be unambiguously attributed to the splitting factor, as the differing frequency of attribute levels in these models could also be the source of difference. Nevertheless, the stated hypotheses made splitting the choice-samples based on affective valence necessary for valid testing.

For future research, a possible solution for this methodological issue is the integration of affective measures as additional choice invariant covariate in the estimation of parameters with a simultaneous consideration of heterogeneity. A control of heterogeneity with respect to the interplay of preference and affect is assumed to be necessary, as not only taste but also affective patterns can differ across individuals (Oliver & Westbrook, 1993).

The results presented here are in line with the general acknowledgement of affect in decision-making (Mellers, 2000; Peters, 2006); moreover, the use of DCEs as a vehicle to analyze preference decisions yields two benefits. First, the impact of immediate affect is now also shown for sequential preference decisions that were designed to make a systematic tradeoff between attributes. Second, the use of DCEs allowed inferring about the goodness of the fit of behavioral choice models in comparison with choice models based on immediate affect. These comparisons imply not only the functional roles of affect during preference decisions but have also implications for preference construction. Thus, future research is encouraged to utilize immediate affect in preference decisions, especially its indicative role for ambivalence and indifference in dependence of differing task demands (e.g., approach or avoidance induction by different stimuli). This might be especially relevant for the looming methodology of best-worst scaling in preference elicitation (Louviere, Lings, Islam, Gudergan, & Flynn, 2013).

Another interesting aspect of affect in preference decision-making is its role in different stages of decision-making (orientation, evaluation, verification; see Russo & Leclerc, 1994) in order to identify decision strategies accompanied by affective patterns as a means to predict choice construction. For example, a mixture of affect (positive and negative) in the evaluation stage might indicate a tradeoff, whereas a predominant affect (positive or negative) at this stage could indicate the use of a heuristic, and thus preference construction. Overall, the use of facial electromyography opens up a vast amount of possibilities to current investigators of affect in decision-making that should not be disregarded.

Affective valence is important but not the only constituting part of affective experiences during decision-making. Its most prominent complement, affective arousal, is addressed in the following chapter.

5 Affective arousal in consumer decision-making

Affective arousal is a fundamental characteristic of behavior. It can be defined as the neurophysiological basis of all processes in the human organism (Bagozzi, 1991; Groeppel-Klein, 2005). Affective arousal is an important aspect of affect, motivation, information processing, behavioral reactions (Kroeber-Riel, 1979), and thus decision-making. The level of arousal can range from sleeping, to more moderate stages, up to a panic level. Especially the moderate stages of arousal are of importance in consumer research, as consumer products usually neither lead to a panic reaction nor to a sudden deep sleep. A basic distinction is the differentiation between tonic and phasic arousal. Tonic arousal is associated with a relatively long-term state that changes slowly due to continuing stimulus presentation or extreme intensive stimuli. By contrast, phasic arousal constitutes a short-term variation of the arousal level as a response to a specific stimulus. Phasic arousal indicates the human organism's preparedness to react. It is strongly linked to attention, and thus it is assumed to produce an enhanced sensitivity of the organism to process relevant stimuli, while irrelevant stimuli are filtered and discarded. Groeppel-Klein (2005) argues that "phasic arousal might be the driving force for decision-making processes and approach behavior […]" (p. 429).

Early theoretical approaches in arousal research suggest a one-dimensional concept (Duffy, 1972). This early neuropsychological research found that the reticular formation in the brain stem is an essential structure associated with arousal. The reticular formation is a complex network of fibers and cell bodies that are involved in the selection process of sensory information from the central nervous system. All sensory and motor fibers should increase the arousal of the reticular formation, and in turn the reticular formation should activate larger parts of the brain. As empirical findings were not consistent with this assumption of one-dimensionality, a more complex theory of arousal was formulated (Boucsein, 1992; Ledoux, 1989).

5.1 Four-dimensional model of arousal

Boucsein (2012) presented a four-dimensional theoretical framework (see Table 16), based on the insights obtained from neurophysiological and information processing research. The first dimension resembles the abovementioned concept of a one-dimensional approach. The reticular formation generates a wide-ranging activation, in the sense of a vigilant sensation and a ready-to-act state of mind. The second dimension largely encompasses the affective component of arousal, which is labeled affect-arousal system. In this system, attention is increased and approach or avoidance reactions are activated ("fight or flight") by the interplay of hypothalamic responses and the amygdala (known for its significant involvement in affective phenomena; Bechara, Damasio, & Damasio, 2000). Processes of this second dimension lead to negative affect. The function of the third dimension of arousal, the effort system, is assumed to be the facilitation of information processing. The hippocampus that controls the memorization of information is responsible for this system. The control of information processing in this dimension of arousal also controls affective states. The fourth dimension is called the preparatory activation system and basically comprises motivational aspects of arousal. Prospects transfer the individual into a state that is preparing for action. This process is accompanied by positive affect. Especially for consumer decision-making, the second (affect-arousal) and the fourth (preparatory activation) systems are of key relevance (Groeppel-Klein, 2005).

Table 16 - Simplified four-dimensional arousal model of Boucsein (2012).

Arousal dimension	*Physiology change*	*Behavior / experience*
1. General activation	Tonic	Being alert / vigilant feeling
2. Affect-arousal	Tonic (EDA)/ phasic (cardio)	Approach or avoidance reactions ("fight or flight") / negative affect
3. Effort system	Tonic (cardio) / phasic (EDA)	Information processing / control of affect
4. Preparatory activation	Tonic (cardio) / phasic (EDA)	Activation of behavior / positive affect

In line with assumptions of the affect-arousal system and the preparatory activation system, one would assume that higher arousal during consumer decisions indicates a state of alarm, or an incentive state based on consolidated experiences, in the sense of a somatic marker (Damasio, 1994). In the first case, an experience of negative affect would be induced, in the latter a positive feeling. Studies of arousal at the point of sale conducted by Groeppel-Klein (2005) support the notion of arousal as an indicator of somatic markers. She showed that arousal is an important construct to explain buying behavior. Buyers were more aroused than non-buyers.

The results of Reid and Gonzales-Vallejo (2009) support the findings of Groeppel-Klein (2005) as a significant contribution to the explanation of preference ratings (regarding diamonds) could be achieved by integration of skin conductance that indicates arousal. Reid and Gonzales-Vallejo (2009) combined arousal with subjective valence ratings in order to infer approach or avoidance, as arousal alone does not allow for such inferences. This approach could have reduced the uniqueness of psychophysiological recordings, which among others is unbiasedness (Wang & Minor, 2008). In line with this view, a model that included subjectively expressed valence (assessed with the self-assessment manikin, Bradley & Lang, 1994) improved the model significantly more than models enriched with autonomic arousal. The combination of subjective valence ratings with autonomic affect measures might have been biased in the direction of cognitive reflections of the preference ratings and thereby lost their unique unbiased contribution to preference.

Nevertheless, these findings suggest the possibility of an indication of somatic markers based on arousal. Such an indication (regardless of whether it is positive or negative in valence) would point to consolidated experience with the stimulus presented in the decision task (Bechara & Damasio, 2005). Thus, it is assumed that decisions with higher arousal show higher stability than decisions with lower arousal. Hence:

H3.1: Higher arousal during consumer decision-making indicates the existence of somatic markers, and thus higher stability of the expressed preference, which results in higher internal and predictive validity of preference measurement.

5.2 Arousal as a complexity-reducing mechanism

A further function of arousal is the reduction of complexity by means of selective attention, which is implicitly covered by Boucsein's (2012) four-dimensional model of arousal (affect-arousal dimension / effort system), without further elaboration. The foundation of the complexity-reduction notion is Easterbrook's (1959) hypothesis that arousal reduces the number of attributes used in judgment tasks. On that basis, Paulhus and Lim (1994) developed the dynamic complexity model, which addresses the effects of arousal on the retrieval of already consolidated memory during decision-making.

Several sources suggest that the dimensionality of cognitive representations is reduced with higher arousal. For example, Suedfeld, Tetlock, and Ramirez (1977) found that the verbal complexity of politicians decreases dramatically just before overt conflict. In a laboratory study, Driver (1962) could show that artificial threats in war games reduced the cognitive complexity to two dimensions: evaluation and dominance. Several more studies have shown that under pressured conditions, the complexity of judgments steadily decreases from many cues down to the most salient ones (e.g., Wallsten & Barton, 1982). This reduced complexity could be seen as a consequence of decreased working capacity, cue selectivity, or distraction (Eysenck, 1982), but it is not simply a speed-accuracy tradeoff in decision-making. Paulhus and Lim (1994) provide the empirical proof for this notion. They induced arousal with loud white noise (90 dBA) and controlled reaction time in a social similarity ratings task (with liked and disliked acquaintances) in order to account for possible speed-accuracy tradeoffs. Results show that the dimensionality of judgments reduced with higher arousal, despite constant reaction times. Results further indicated that similarity ratings were more extreme in the high-arousal condition, which was indicated by a higher variance of the ratings. Higher extremity of similarity ratings in higher arousal is explained by the reduction in one dimension: evaluation. As other dimensions contribute less, the synthesis of less information leads to a predominance of evaluative information, which polarizes the judgments (Paulhus & Lim, 1994).

Translated to consumer decision-making the dynamic complexity model would predict a focus of attention toward the most salient attributes of products. Furthermore, there should be greater variance of attribute utility overall, due to more extreme judgments. Contrary to the interpretation of arousal in consumer decisions based on the affect-arousal and preparatory activation systems of Bucsein's (2012) four-dimensional model, the dynamic complexity model suggests opposing effects of arousal on consumer choice:

H3.2: Higher arousal in a consumer choice will lead to a reduction of complexity, and thus to a decreasing number of significant attributes, and a higher variance of attribute utilities. Overall, this should lead to a lower internal and predictive validity.

5.3 Arousal and effort in decision-making – an inverted U-shape

The results of a study conducted by Arana and Leon (2009) suggest a non-linear interrelation of affective arousal and performance in consumer decision-making. Their study is driven by interest in the role of the individual's affective state during the choice of a decision rule. As affect impacts numerous aspects of the choice process, including creativity (Isen, Johnson, Mertz, & Robinson, 1985), problem-solving abilities (Isen, Daubman, & Nowicki, 1987), cognitive flexibility (Dovidio, Kawakami, Johnson, Johnson, & Howard, 1997), consumer attitudes, and purchase intentions (Kahn & Luce, 2003), they assume an impact of affect on the decision rules that are used to choose an option. Specifically, they wanted to determine the extent to which individuals depart from purely compensatory heuristics due to affective states. In a nutshell, they were interested in how affect impacts strategy selection in DCEs. Therefore, they measured the affective intensity during a stated preference task, which is related to a real-world problem the participants were faced with: solving pollution problems caused by a stone-mining company in the neighborhood. The use of heuristics was measured with a verbal protocol that was elicited with the thinking-aloud technique. To ensure data quality, the protocols were transcribed and evaluated by two judges, who were unaware of the hypotheses (inter-rater agreement was 0.91). Amongst others, the subjectively measured intensity of affect was regressed on these decision-rule ratings. Results indicate that choosing a linear compensatory rule increases with affective intensity, but with a decreasing rate, reaching its maximum at some level but not at the higher bounds. Thus, a quadratic or inverse U-shaped form of the relationship of affective intensity and the degree of compensation is suggested. Arana and Leon (2009) interpret this result in line with evidence that affective intensity has an inverse U-shaped impact on task performance.

This phenomenon, labeled the Yerkes-Dodson law (Yerkes & Dodson, 1908), predicts that behavior of a person with very low and very high affective intensity levels is driven by a tendency to spend little energy on information gathering and problem solving, and thus do not perform optimally (Kaufman, 1999). Too little arousal leads to downsized information gathering and problem solving. In this case, attention is devoted to other tasks than the task at hand. Memory is blocked by obsessive thoughts or is used for rumination on non-task considerations (e.g., Baker & Channon, 1995). Too much arousal is associated with a reduction of effort for decision-making (Eysenck, 1982). More specifically, high levels of arousal block access to short-term memory and disrupt logical or inferential thought processes. Rational considerations of cost and benefit (linear tradeoffs) are blocked, and aggression or violence are promoted (e.g., Lazarus, 1991). In contrast to these suboptimal levels of arousal, optimal arousal increases the effort dedicated to information gathering and problem solving (Kahneman, 1973). Mental focus is narrowed to the relevant problems, and recall from short-term memory is improved during optimal levels of arousal (Revelle & Loftus, 1990). Although it is not assumed that customers experience extreme levels of low (depression, boredom) and high (fear, mad desire) arousal during product decisions, the detrimental effects are assumed to be active, though in a lessened manner. The findings presented in accordance with the Yerkes-Dodson law lead to a third possible effect of affective arousal on the quality of consumer decision-making.

H3.3: High and low arousal in consumer choice will lead to inappropriate information processing and thus should lead to a lower internal and predictive validity, as compared with moderate arousal.

With regard to the role of arousal in consumer decision-making, the three hypotheses test differing theories, but only the somatic marker and the complexity reduction theories are actually exclusive. Relating to the inverse U-shaped relationship between decision performance and arousal, it might be possible that high affective arousal indicates sub-optimal decision behavior and / or complexity reduction. Nevertheless, it is important to respect the presumed and sometimes subtly different effects of arousal, and scrutinize them in order to gain a more holistic picture of the role of arousal in consumer decision-making.

5.4 Empirical investigation of affective arousal in consumer choice

As a complement to the exploration of affective valence, the following subsection will address the impact of arousal on preference decision-making in discrete choice experiments. As arousal can be defined as the neurophysiological basis of all processes in the human organism (e.g., Groeppel-Klein, 2005), it should also have a significant impact on the process and the outcome of preference decision-making (Reid & Gonzales-Vallejo, 2009). The predictions of the three models of arousal, four-dimensional model of arousal (Boucsein, 2012), complexity reduction (Paulhus & Lim, 1994), and Yerkes-Dodson law (Yerkes & Dodson, 1908) will be scrutinized in detail. The methodological setup to explore arousal in DCEs is identical to the setup of the exploration of affective valence in DCEs in matters of data collection, except for the measurement of arousal.

5.4.1 Method

The following overview of the methods section is primarily a recap, as the study to collect the data is identical to that presented in Chapter 4. The difference to the study concerned with affective valence is the sound description of the measurement of arousal with skin conductance response.

Forty-nine students of the University of Hamburg who responded to posted flyers or e-mail invitations participated in this laboratory study for an hourly wage of 10 EUR. Participants were fluent in German, healthy, and were not taking any medication that might affect affective functioning (e.g., antidepressants). Some 53.1 % (n = 26) of the participants were female. The mean age of the participants was 24.8 (SD = 3.5). Three sets of stimuli were used in three discrete choice experiments (Louviere & Woodworth, 1983) to increase the generalizability of the results: charity, face, and yogurt options. All three stimuli types were described by three attributes with two levels each (see Table 17; see Appendix D for the full set of options).

Table 17 - Attributes and attribute levels of charity, face, and yogurt stimuli.

	Stimulus 1: Charity options	Attribute levels	
Attributes	Living conditions	Bad	Moderate
	Family size	6 people	3 people
	Willingness to learn	Low	Average
	Stimulus 2: Face options	Attribute levels	
Attributes	Eyes	Small	Big
	Nose	Small	Big
	Mouth	Small	Big
	Stimulus 3: Yogurt options	Attribute levels	
Attributes	Fat content	1.5%	3.5%
	Taste	Apricot	Strawberry
	Label	Best standard	Organic

The full-factorial combination of attributes and attribute levels produces a 2 x 2 x 2 factorial or eight option descriptions per stimulus type. These eight alternatives were assigned to 12 choice sets, each with two options. The choice set design is orthogonal and balanced, as suggested by Street and Burgess (2004).

Participants were asked for certain exclusion criteria that could disturb the measurement of skin conductance response (particular medications, alcohol, nicotine abuse, caffeine abuse, etc., were not allowed), and demographic questions. Participants were asked to sit in a comfortable chair in an attenuated and dimly lit room. Instructions and stimuli were presented on a 17'' monitor placed approximately 70 cm in front of the participants. As arousal was measured with skin conductance response (SCR, Boucsein, 1992), the physiological recording equipment was attached to each subject's non-dominant hand (Fowles et al., 1981).

Following the setup, the experimental procedure lasted approximately 50 minutes. A computer program presented instructions and choice sets to the participants (Presentation, Neurobs Inc.). Synchronized event markers were used to align SCR data and behavioral choices (indicated by the press of a button). Participants received a short instruction that included practice on how to use the choice buttons, the stimulus presentation, and the attributes and attribute levels of each stimulus type. A 2-second fixation-cross was presented for alignment of initial visual attention and baseline correction of SCR measures. Choice sets were presented without time limit, with each presentation ending by choice (button press).

After each choice, respondents received a 10-second rest period to regain an affective baseline, and then they progressed at their own pace. Figure 12 shows the course of action in a choice set.

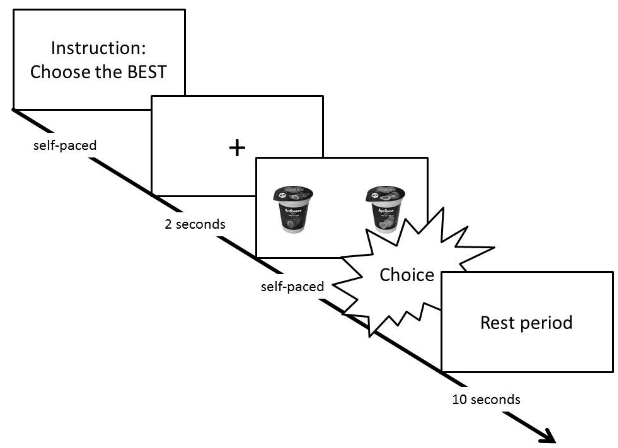


Figure 12 - Course of a choice set with skin conductance response measurement.

The presentation of the three discrete choice experiments started with face options, followed by charity options, and ended with yogurt options. Between the three DCEs, control questions and stimulus-accordant holdout tasks were presented (four options had to be ranked by preference). During the DCEs, arousal was measured via skin conductance response.

5.4.1.1 Measurement of arousal with SCR

SCR is a specific type of measurement of electrodermal activity (EDA) in response to an event (e.g., products appearing on a screen). EDA is now commonly used and accepted as a measure of arousal with the amplitude of conductance responses serving as an arousal index (Blascovich et al., 1993). Lang et al., (1993) report a significant positive linear relationship between arousal and SCR, utilizing the international affective picture system. Öhman, Esteves, Flykt, and Soares, (1993) have proposed that affect can be defined in a two-dimensional space of approach / avoidance and arousal. This claim is empirically supported, as the arousal dimension is independent of the approach/avoidance dimension and is aptly captured with EDA recordings (Öhman et al., 1993). In two studies, Detenber, Simons, and Bennett (1998) found that SCR was related to the arousal properties of images and did not discriminate valence.

The SCR measurement was taken from the non-dominant hand due to comparability of the thickness of the cornea (hard skin) between individuals. SCR was recorded with a sampling rate of 2 kHz at the skin surface of participants using SCR100c 8 mm electrodes with electrode gel and amplified using a V-AMP amplifier by BrainProducts. A bipolar placement of the electrodes was used on the thenar and hypo-thenar areas of the palm. The palm of the hand is the area that is the best suited for measuring skin conductance as it contains a high density of eccrine sweat glands (thermoregulative sweat glands). The EDA electrode sites were abraded with abrasive paste and isopropyl alcohol pads prior to the placement of electrodes. A constant voltage procedure (0.5 volt) passing a 1 Hz signal between the two electrode sites was used to render conductance-related changes due to dermal response to stimulus presentation. The gain on the V-AMP amplifier was set at 5 mS/V. Figure 13 illustrates the placement of electrodes on the palm.

Figure 13 - Placement of skin conductance response electrodes on thenar (left electrode) and hypo-thenar (right electrode) areas of the palm.

Reduction of the electrodermal signal into SCR followed the recommendations for electrodermal measurements published by the Society for Psychophysiological Research (Fowles et al., 1981). Raw signals were filtered with a 1 Hz low-pass filter (no high-pass filter) to reduce noise in the measurement of arousal. Figure 14 depicts the filtered skin conductance signal with affective arousal.

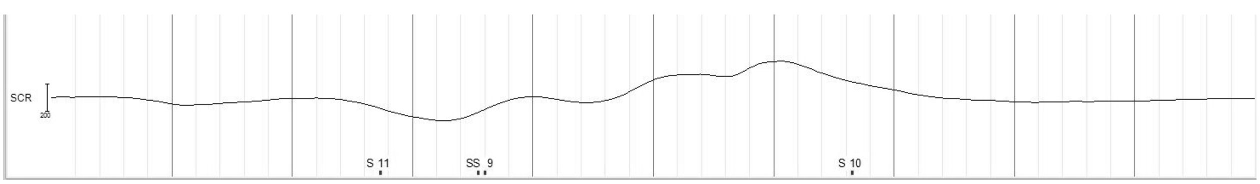


Figure 14 - Filtered skin conductance signal with affective arousal between markers "S11" (start of the trial) and "S10" (end of the trial).

In this study, the most common arousal indicator, the SCR magnitudes, reflecting the peak amplitude of the SCR, was used. In order to quantify these magnitudes, the peak amplitude of this SCR was calculated as the difference between rectified skin conductivity before the stimulus onset (1 sec baseline measure) and the skin conductivity at the peak of the SCR (Boucsein, 1992). SCR magnitudes were standardized within each participant, as the magnitude of skin conductance data can vary between participants. This is not only due to psychological but also physiological causes, such as the thickness of the cornea (Dawson, Schell, & Filion, 2000). See Appendix C for details of SCR measurement and analysis.

5.4.1.2 Data

In total, 588 choices from 49 participants (49 participants x 12 choices) were observed in each stimulus type (charity, faces, yogurts). An overview of the skin conductance responses across choice sets in each stimulus type shows no distinct habituation effects across the 12 choice sets per stimulus type (see Figure 15).

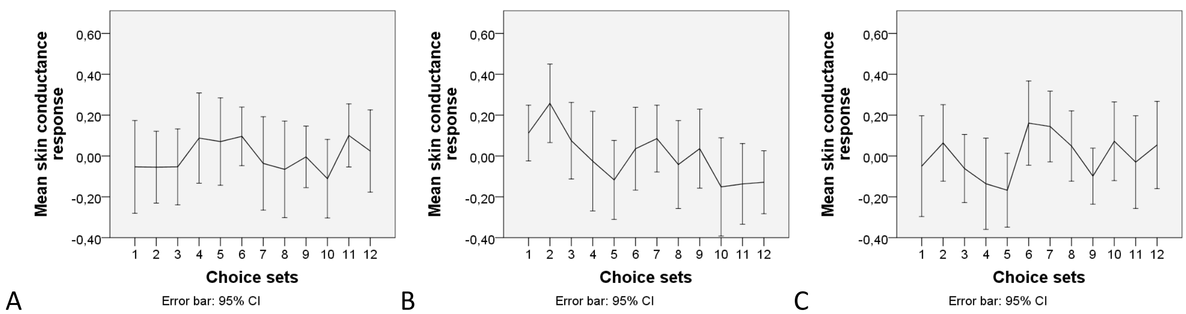


Figure 15 - Skin conductance response of all respondents across all 12 choice sets per stimulus material (A = charity; B = faces; C = yogurts).

5.4.2 Results

For hypothesis testing, choice samples are split in half based on the median / quartiles of the SCR values. Thus, there is a high and low arousal choice sample. As these samples have the same number of observations (588 / 2 = 294; median split) and the same number of parameters (6), one can use the likelihood ratio test suggested by Swait and Louviere (1993) to compare choice models with either high or low SCR values.

As the splitting of the models could result in an unbalanced choice design, the balance was tested. Results show that the frequency of particular choice sets between the divided samples does not differ significantly (see Table 18).

Table 18 - Check of balance (comparable frequencies of choice sets) in split samples of choices based on SCR values.

Split samples of choices	Chi-square value (df)	P-value
Charity decisions		
High vs. low arousal	12.98 (11)	0.295
High / low vs. moderate arousal	12.49 (119	0.328
Face decisions		
High vs. low arousal	15.89 (11)	0.157
High / low vs. moderate arousal	11.83 (11)	0.376
Yogurt decisions		
High vs. low arousal	10.69 (11)	0.469
High / low vs. moderate arousal	7.59 (11)	0.749

Conditional logit models (e.g., McFadden, 1974) based on behavioral choices, as well as choice models with either high or low arousal, are compared with each other in order to examine the hypotheses. The holdout prediction as predictive validity indicator correlates predicted ranks, based on model estimates, with empirically derived preference ranks in a holdout task.

The significant likelihood ratio test statistic indicates that the arousal measure does explain a meaningful part of variance in the behavioral choice mode for charity decisions (see Table 19). The results for internal validity (indicated by BIC and adjusted pseudo-R^2; see Kass & Raftery, 1995) suggest that the model based on choices with high arousal shows lower internal validity, which is in line with H3.2 (complexity reduction). By contrast, predictive validity is higher in the high arousal model. Thus, H3.1 (somatic markers) is supported for predictive validity but not for internal validity. H3.2 (complexity reduction), however, is supported for internal validity but not predictive validity.

Table 19 – Choice models with higher and lower affective arousal in charity decisions.

	Behavioral choice		High arousal		Low arousal	
	Par.	SE	Par.	SE	Par.	SE
Living cond. – bad	**1.33*** **	0.11	**1.31*** **	0.16	**1,37*** **	0.15
Living cond. – moderate	**-1.33*** **		**-1.31*** **		**-1.37*** **	
Family size – 3	**-0.40*** **	0.09	**-0.50*** **	0.14	**-0.27* **	0.14
Family size – 6	**0.40*** **		**0.50*** **		**0.27* **	
Will. learn – avg.	**-0.96*** **	0.09	**-0.99*** **	0.14	**-0.95*** **	0.14
Will. learn – low	**0.96*** **		**0.99*** **		**0.95*** **	
Living X Family – diff.	0.15	0.09	0.11	0.14	0.21	0.14
Living X Family – same	-0.15		-0.11		-0.21	
Living X Learn – diff.	-0.01	0.09	0.02	0.14	-0.09	0.13
Living X Learn – same	0.01		-0.02		0.09	
Family X Learn – diff.	-0.01	0.10	0.12	0.16	-0.15	0.15
Family X Learn – same	0.01		-0.12		0.15	
Statistics						
Nobs	588		294		294	
No. of parameters	6		6		6	
LN likelihood	-195.35		-101.63		-91.11	
LR test	Crit. χ^2 (α=.05; df=1) = 3.84		5.21			
BIC	414.05		226.61		205.58	
Adj. pseudo-R^2(0)	0.60		0.56		0.65	
Holdout prediction	0.75		0.75		0.73	

(*** = p < .001; ** = p < .01; * = p < .05)

The likelihood ratio test suggests that arousal in face decisions is a meaningful factor to divide all choices into two samples. In this stimulus type, choices with high arousal show higher internal validity but lower predictive validity (see Table 20). Thus, H3.1 (somatic markers) is supported for internal validity but not for predictive validity. The predictive validity reaches meaningfulness in the model based on choices with low arousal; thus, H3.2 (complexity reduction) is partly supported for predictive validity and not for internal validity. Interestingly, the validity pattern for charity decisions is the opposite of the validity pattern for face decisions.

Table 20 – Choice models with higher and lower affective arousal in face decisions.

	Behavioral choice		High arousal		Low arousal	
	Par.	SE	Par.	SE	Par.	SE
Eyes – small	**-0.34*** **	0.05	**-0.45*** **	0.08	**-0.26*** **	0.07
Eyes – big	**0.34*** **		**0.45*** **		**0.26*** **	
Nose – small	**0.23*** **	0.05	**0.28*** **	0.08	**0.20** **	0.07
Nose – big	**-0.23*** **		**-0.28*** **		**-0.20** **	
Mouth – small	-0.04	0.05	0.01	0.07	-0.11	0.08
Mouth – big	0.04		-0.01		0.11	
Eyes X Nose – diff.	**-0.16** **	0.05	**-0.17* **	0.08	-0.14	0.08
Eyes X Nose – same	**0.16** **		**0.17* **		0.14	
Eyes X Mouth – diff.	**-0.15** **	0.05	**-0.21** **	0.08	-0.09	0.07
Eyes X Mouth – same	**0.15** **		**0.21** **		0.09	
Nose X Mouth – diff.	**0.20*** **	0.05	**0.24** **	0.08	**0.18* **	0.07
Nose X Mouth – same	**-0.20*** **		**-0.24** **		**-0.18* **	
Statistics						
Nobs	588		294		294	
No. of parameters	6		6		6	
LN likelihood	-365.51		-177.02		-185.92	
LR test	Crit. χ^2 (α=.05; df=1) = 3.84		5.12			
BIC	754.37		377.39		395.20	
Adj. pseudo-R^2(0)	0.13		0.17		0.11	
Holdout prediction	-0.03		-0.03		0.04	

(*** = p < .001; ** = p < .01; * = p < .05)

Regarding yogurt decisions, the likelihood ratio test indicates significance of the arousal measure as a splitting factor. Internal validity measures indicate that the choice model with high arousal performs better than the model with low arousal (see Table 21). As the predictive validity measures do not differ between the arousal models, H3.1 (somatic markers) is only partly supported for internal validity. The results do not support H3.2 (complexity reduction).

Table 21 – Choice models with higher and lower affective arousal in yogurt decisions.

	Behavioral choice		High arousal		Low arousal	
	Par.	SE	Par.	SE	Par.	SE
Taste – apricot	**-0.17***	0.05	**-0.18***	0.07	**-0.16***	0.07
Taste – strawberry	**0.17***		**0.18***		**0.16***	
Fat content – 1.5%	0.03	0.05	0.02	0.07	0.04	0.07
Fat content – 3.5%	-0.03		-0.02		-0.04	
Label – best standard	**-0.47***	0.06	**-0.53***	0.08	**-0.41***	0.08
Label – organic	**0.47***		**0.53***		**0.41***	
Taste X Fat content – diff.	-0.04	0.06	-0.01	0.08	-0.06	0.08
Taste X Fat content – same	0.04		0.01		0.06	
Taste X Label – diff.	-0.01	0.05	0.07	0.07	-0.09	0.07
Taste X Label – same	0.01		-0.07		0.09	
Fat content X Label – diff.	0.02	0.05	0.01	0.08	0.04	0.07
Fat content X Label – same	-0.02		-0.01		-0.04	
Statistics						
Nobs	588		294		294	
No. of parameters	6		6		6	
LN likelihood	-363.65		-176.93		-184.62	
LR test	Crit. χ^2 (α=.05; df=1) = 3.84		4.18			
BIC	750.65		377.21		392.61	
Adj. pseudo-R^2(0)	0.14		0.17		0.12	
Holdout prediction	0.53		0.53		0.53	

(*** = p < .001; ** = p < .01; * = p < .05)

In summary, the somatic marker hypothesis (H3.1) is partly supported for internal validity in face and yogurt decisions, and for predictive validity in charity decisions. The complexity reduction hypothesis (H3.2) is partly supported for internal validity in charity decisions, and for predictive validity in face decisions.

The following results focus on H3.3, which is concerned with the inverse U-shaped relationship between affective arousal and compensatory decision-making.

The meaningfulness of the differentiation between higher / lower and moderate arousal in charity decisions is indicated by the significant likelihood ratio test (see Table 22). Furthermore, the model based on choices with moderate arousal outperforms the higher / lower arousal model for internal and predictive validity. Thus, the assumption that high / low arousal in consumer choice will lead to inappropriate information processing, and thus to a lower internal and predictive validity compared with moderate arousal (H3.3), is supported by the results of charity decision-making.

Table 22 – Choice models with higher / lower and moderate affective arousal in charity decisions.

	Behavioral choice		High / low arousal		Moderate arousal	
	Par.	SE	Par.	SE	Par.	SE
Living cond. – bad	**1.33*** **	0.11	**1.24*** **	0.14	**1.50*** **	0.18
Living cond. – moderate	**-1.33*** **		**-1.24*** **		**-1.50*** **	
Family size – 3	**-0.40*** **	0.09	**-0.28* **	0.12	**-0.57*** **	0.16
Family size – 6	**0.40*** **		**0.28* **		**0.57*** **	
Will. learn – avg.	**-0.96*** **	0.09	**-0.94*** **	0.13	**-1.03*** **	0.16
Will. learn – low	**0.96*** **		**0.94*** **		**1.03*** **	
Living X Family – diff.	0.15	0.09	0.17	0.13	0.05	0.16
Living X Family – same	-0.15		-0.17		-0.05	
Living X Learn – diff.	-0.01	0.09	0.15	0.12	-0.25	0.16
Living X Learn – same	0.01		-0.15		0.25	
Family X Learn – diff.	-0.01	0.10	-0.03	0.14	0.06	0.18
Family X Learn – same	0.01		0.03		-0.06	
Statistics						
Nobs	588		294		294	
No. of parameters	6		6		6	
LN likelihood	-195.35		-105.62		-85.47	
LR test	Crit. χ^2 (α=.05; df=1) = 3.84		8.49			
BIC	414.05		234.60		194.30	
Adj. pseudo-R^2(0)	0.60		0.56		0.65	
Holdout prediction	0.75		0.73		0.75	

(*** = p < .001; ** = p < .01; * = p < .05)

Although the significant likelihood ratio test indicates that the dividing factor is meaningful, there are no meaningful differences related to internal (BIC) and predictive validity (holdout prediction) for choice models based on higher / lower or moderate arousal in face decision (see Table 23). Thus, H 3.3 cannot be confirmed for face decisions.

Table 23 – Choice models with higher / lower and moderate affective arousal in face decisions.

	Behavioral choice		High / low arousal		Moderate arousal	
	Par.	SE	Par.	SE	Par.	SE
Eyes – small	**-0.34*****	0.05	**-0.30*****	0.08	**-0.37*****	0.07
Eyes – big	**0.34*****		**0.30*****		**0.37*****	
Nose – small	**0.23*****	0.05	**0.21****	0.07	**0.26*****	0.08
Nose – big	**-0.23*****		**-0.21****		**-0.26*****	
Mouth – small	-0.04	0.05	-0.07	0.07	-0.03	0.08
Mouth – big	0.04		0.07		0.03	
Eyes X Nose – diff.	**-0.16****	0.05	**-0.26*****	0.07	-0.04	0.08
Eyes X Nose – same	**0.16****		**0.26*****		0.04	
Eyes X Mouth – diff.	**-0.15****	0.05	**-0.16***	0.07	-0.13+	0.08
Eyes X Mouth – same	**0.15****		**0.16***		0.13+	
Nose X Mouth – diff.	**0.20*****	0.05	**0.19***	0.08	**0.21****	0.08
Nose X Mouth – same	**-0.20*****		**-0.19***		**-0.21****	
Statistics						
Nobs	588		294		294	
No. of parameters	6		6		6	
LN likelihood	-365.51		-181.69		-181.22	
LR test	Crit. χ^2 (α=.05; df=1) = 3.84		5.17			
BIC	754.37		386.74		385.80	
Adj. pseudo-R^2(0)	0.13		0.14		0.14	
Holdout prediction	-0.03		-0.03		-0.03	

(*** = p < .001; ** = p < .01; * = p < .05; + = p < .10)

In yogurt decisions, not only do the internal and predictive validity measures not show any difference, but the likelihood ratio test also suggests that the higher / lower vs. moderate arousal factor does not make sense as a dividing factor (see Table 24). H3.3 cannot be confirmed for yogurt decisions.

Table 24 – Choice models with higher / lower and moderate affective arousal in yogurt decisions.

	Behavioral choice		High / low arousal		Moderate arousal	
	Par.	SE	Par.	SE	Par.	SE
Taste – apricot	**-0.17*** **	0.05	**-0.16***	0.07	**-0.17***	0.07
Taste – strawberry	**0.17*** **		**0.16***		**0.17***	
Fat content – 1.5%	0.03	0.05	-0.01	0.07	0.08	0.07
Fat content – 3.5%	-0.03		0.01		-0.08	
Label – best standard	**-0.47*** **	0.06	**-0.47*** **	0.08	**-0.46*** **	0.08
Label – organic	**0.47*** **		**0.47*** **		**0.46*** **	
Taste X Fat content – diff.	-0.04	0.06	-0.01	0.08	-0.06	0.08
Taste X Fat content – same	0.04		0.01		0.06	
Taste X Label – diff.	-0.01	0.05	-0.01	0.07	-0.02	0.07
Taste X Label – same	0.01		0.01		0.02	
Fat content X Label – diff.	0.02	0.05	0.07	0.08	-0.03	0.07
Fat content X Label – same	-0.02		-0.07		0.03	
Statistics						
Nobs	588		294		294	
No. of parameters	6		6		6	
LN likelihood	-363.65		-181.93		-180.71	
LR test	Crit. χ^2 (α=.05; df=1) = 3.84		0.19			
BIC	750.65		387.22		384.79	
Adj. pseudo-R^2(0)	0.14		0.14		0.14	
Holdout prediction	0.53		0.53		0.53	

(*** = p < .001; ** = p < .01; * = p < .05)

5.4.3 Discussion

The splitting of behavioral choice samples in choices with high and low arousal based on skin conductance measures allows a closer look at the function of arousal during consumer decision-making in a discrete choice context. Overall, results suggest that arousal does have an impact on preference decision-making, but only partly as expected.

Findings that indicate the function of arousal as a marker of value (e.g., Beachara & Damasio, 2005; Reid & Gonzales-Vallejo, 2009) that is based on prior experience, can only be supported by internal validity measures in face and yogurt decisions, and predictive validity measures in charity decisions. The opposing hypothesis, which assumes that high arousal leads to complexity reduction (Paulhus & Lim, 1994), is confirmed for predictive validity in face decisions, and internal validity in charity decision.

As the assumptions hold only for certain stimulus types for either short-term or longer-term preference stability, there seems to be an interaction between the stimulus type and arousal during decision-making.

Regarding the short-term stability of preferences (internal validity), arousal cannot have an impact when there is not enough pre-knowledge about the stimulus type, in other words, when there are no somatic markers because there is no or not enough prior experience. This might be the reason for the refutation of the somatic marker hypothesis for internal validity in charity decisions. A post hoc analysis shows that individuals have significantly less pre-knowledge with respect to charity options, compared with face and yogurt options ($t(48) = 3.27$, $p = .002$ for charity vs. faces, and $t(48) = 4.87$, $p < .001$ for charity vs. yogurts, and $t(48) = 1.60$, $p = .115$ for faces vs. yogurts; pre-knowledge was measure with four items; Cronbach's alpha of .81, see Appendix A for details). Thus, arousal in charity decisions indicated complexity reduction, as there was no prior experience with that kind of decision, and in face and yogurt decisions, arousal indicated somatic markers.

The impact of arousal during decision-making on longer-term stability (predictive validity) can also be differentiated based on the prior (non-)existence of somatic markers. When there were no prior somatic markers (charity), arousal could indicate the process of prototypic somatic marker development. On the other hand, in the case of already acquired somatic markers (faces and yogurts), arousal indicates the use and probably the concurrent re-structuring of the somatic markers (used memory content is always changed; see Weber & Johnson, 2009). The former case describes an initial learning based on choices with higher arousal; the latter describes additional learning based on choices with higher arousal. The initial learning should lead to higher predictive validity, as there is less chance of memory content to interfere, whereas additional learning should lead to lower predictive validity, due to a higher chance of memory processes to interfere (M. C. Anderson, 2003). Thus, the assumption of somatic markers indicated by higher arousal is more likely, when prior knowledge is existent; otherwise, arousal might indicate the development of prototypic somatic markers. As far as complexity reduction is concerned (Paulhus & Lim, 1994), it is possible that the additional learning or restructuring of somatic markers be conducted by a reduction of complexity indicated by arousal, which would ultimately lead to less longer-term stability of preference expression.

In summary, both competing assumptions (somatic marker and complexity reduction) are relevant, but they depend on the prior (non-)existence of somatic markers.

The assumed inverse U-shaped relationship between arousal and preference stability (f.ex., Arana & Leon, 2009) was supported by results for charity decisions but not for yogurt and face decisions. In the case of less pre-knowledge (charity), high arousal indicated a reduction of effort for decision-making, as inferential thought processes might have been blocked (Eysenck, 1982), and low arousal led to less information gathering and problem solving (Baker & Channon, 1995).

It seems that the optimal level of arousal shifts over the course of sub-sequential decision-making when there is more pre-knowledge (for faces / yogurts) compared with less pre-knowledge (for charity decisions). The interaction for the optimal level of arousal with task difficulty is addressed by Broadhurst (1959) and Anderson (1994). Their research suggests a negative monotonic relationship between optimal arousal and task difficulty, i.e., the more difficult a task, the lower the optimal arousal. Thus, the charity task could have been more difficult due to less prior knowledge, and a consistently optimal (low) level of arousal existed. Face and yogurt decisions were presumably easier tasks due to more pre-knowledge in which a consistent optimal level of arousal assumedly did not exist. Limiting this interpretation is the post hoc finding that faces were perceived as most difficult ($M = 2.9$), followed by charity options ($M = 3.2$, difference to faces $t(48) = -1.8$; $p = .07$), and yogurt decision were perceived as easiest ($M = 4.2$, difference to faces: $t(48) = -7.7$; $p < .001$, see Appendix A for measurement details). Thus, further tests of the function of arousal in preference decision-making should experimentally vary task difficulty and motivation (Anderson, 1994) in order to gain a clear picture of the optimal arousal level.

5.5 Summary and outlook of affective arousal in consumer decision-making

Affective arousal as a fundamental characteristic of behavior also influences preference decision-making in DCEs. A test of two competing functional models of arousal (somatic marker and complexity reduction) suggested that both models strongly interact with possibly moderating factors such as pre-knowledge of stimuli. Nevertheless, both models also contribute to an explanation of the function of arousal in preference decisions; however, refinement is needed. Arousal undoubtedly also indicates preference construction, either due to the indicated non-existence of prior experience (Bechara & Damasio, 2005; no somatic markers), the reduction of complexity when additional information interferes with existent information (Paulhus & Lim, 1994), or the (non-)optimal levels of arousal during preference decisions (e.g., Kaufman, 1999). Therefore, arousal is to be seen as an alterable window onto the master list of preference, whereas somatic markers, complexity reduction, and optimal arousal are potential openers to that window.

Theoretically, results are valuable, as the impact of arousal on the process of preference decision-making is detectable, but the practical implications are rather low. Especially the differences in holdout prediction (predictive validity) of the choice models based on varying arousal-related factors are fairly small. The differences range from zero to 0.07, whereas a level of 0.1 would indicate meaningfulness (see Cohen, 1992). The response mode of the holdout prediction task (ranking) differed from the response mode of the preference elicitation task (choices). The variation of response mode could be one reason for the overall low differences regarding holdout prediction of complementing arousal-related choice models. Changes in response mode can already lead to preference construction (Payne et al., 1999a; Schkade & Johnson, 1989), which possibly masked effects concerned with arousal. In order to control for effects of response mode, future research should use the same response mode in a holdout prediction task and in the preference elicitation task. A further control of probable effects of arousal on preference construction in the holdout task would complete a sound testing of predictive validity.

Furthermore, the change of parameter estimates in choice models with high (high / low) and low (moderate) arousal is mostly marginal. An exception is the model with moderate arousal for charity decisions, which indicates the potential of the integration of arousal in DCE analysis. Besides the already discussed factors for higher or lower impact of arousal, the affective potency of the stimulus material might also play a role that should not be neglected, as charity decisions might have been perceived as far more serious than face and yogurts decisions.

In short, it is important to consider arousal in DCE-like preference decisions, but this seemingly easy construct is nevertheless hard to tackle. This study of arousal indicates that this latent factor can have a multitude of meanings that vary according to many moderating factors. Thus, future work should systematically vary pre-knowledge, task motivation and task difficulty of stimuli in use in DCEs to gain a deeper understanding of the role of arousal in DCEs, and thus of preference construction.

6 Joint impact of affective valence and arousal in consumer decision-making

Up to this point, this work has focused on the separate impacts of affective valence and affective arousal. The differentiation between affective arousal and affective valence is subtle but important in the research of consumer behavior, as both might have different cognitive functions and thus behavioral consequences (e.g., Gorn, Pham, & Sin, 2001). Although the dissociation of affective arousal and affective valence is a powerful means to gain clarification in theoretical and empirical work concerned with affect (Russell, Weiss, & Mendelsohn, 1989), this separation is somewhat artificial. Affect is a holistic phenomenon during decision-making, as all functions of affect (related to valence and arousal) will be synchronized during this process (Scherer, 2005).

Valence and arousal, the fundamental dimensions of affect, are thought to play an essential role in assigning value to decision options (Ellen Peters, Västfjäll, Gärling, & Slovic, 2006). Valence and arousal capture most of the variance in self-reported mood ratings (Barrett & Russell, 1999). In addition, cross-cultural studies (R. J. Larsen & Diener, 1992), neuropsychological (Posner et al., 2009), and developmental psychology (Russell & Bullock, 1985) point out that valence and arousal are core components of affective states. Thus, the following examinations account for the holistic concept of affect by jointly considering valence and arousal.

6.1 Relation between valence and arousal

Suri, Sheppes, and Gross (2013) predicted affective choice with a model that tested the impact of valence only, a model with equal weights for valence and arousal, and an empirically derived best-fit model. In a pre-study, they asked participants to rate a set of affective pictures (IAPS; international affective picture system, developed by Lang, Bradley & Cuthbert, 1999) for valence, arousal, and wanting. Valence and arousal ratings were regressed on the wanting ratings in order to gain metric impacts. These impact parameters of valence and arousal were used in subsequent studies as the best-fit model for choice prediction. In order to allow prediction by the models, participants first had to rate different options (IAPS pictures and headlines of stories). Then, the rated options were presented again in choice pairs. Actual choices were now compared with choices based on assumptions of the three different models: valence-only, equal-weights model, or empirical best-fit model. Whereas the best-fit model predicted around 75% of all choices correctly, the equal-weights model predicted around 68%, and the worst model, the valence-only model, predicted around 62% of all choices correctly (50% would be chance level). Thus, Suri et al. (2013) could show that valence *and* arousal have a meaningful impact on choice, more than valence alone. Furthermore, arousal has a lesser impact than valence, which is derived from the impact parameters of the best-fit model.

The theoretical background of a combined influence of valence and arousal on preference is limited to theoretical developments on approach and avoidance motivation (Watson & Tellegen, 1985). This research suggests that approach and avoidance bisect the orthogonal valence and arousal dimensions, and thus valence and arousal contribute in equal measure to approach and avoidance (Watson, Wiese, Vaidya, & Tellegen, 1999). An opposing view suggests that only valence matters for approach and avoidance (Bower, 1991; Elster, 1998). The theoretical background is rather explorative, especially in the context of consumer decisions considered here. The empirical results of Suri et al. (2013) are persuasive, however, and thus the following explorative research question is stated:

Explorative research question 1: Does either valence or arousal alone or arousal and valence together explain consumer choice?

As immediate autonomic affect is used in this study as additional data to consumer choice, probable biases of affective self-reports (carry-over on wanting measure, unreliable affect measure; see Wang & Minor, 2008) might be reduced and thus open another window onto constructive processes of affect in consumer choice (see discussion in Suri et al., 2013, p. 632).

6.2 Discrete affect in consumer choice

A further interesting approach to the combined impact of valence and arousal is the inference of discrete affect in consumer decision-making based on valence and arousal. Pfister and Böhm (2008) declare that the consideration of valence and arousal is an oversimplification. Discrete affect programs (basic emotions) might have finer-grained impacts on cognitive processes, which are not captured by this two-dimensional approach. Several studies suggest that discrete affect rather than valence and arousal drives depth-of-processing effects (Loewenstein & Lerner, 2003; Tiedens & Linton, 2001). In a series of studies, Tiedens and Linton (2001) showed that emotions characterized by certainty (e.g., contentment, anger) lead decision-makers to rely on heuristics, whereas emotions characterized by uncertainty (e.g., worry, surprise) lead to careful scrutiny of decision information. Certainty as a decision dimension had more meaningful incremental explanatory power than the valence dimension alone. Although sadness and anger share the same affective valence (negative), anger triggered heuristic decision processes, and sadness did not (see also Bodenhausen, Sheppard, & Kramer, 1994).

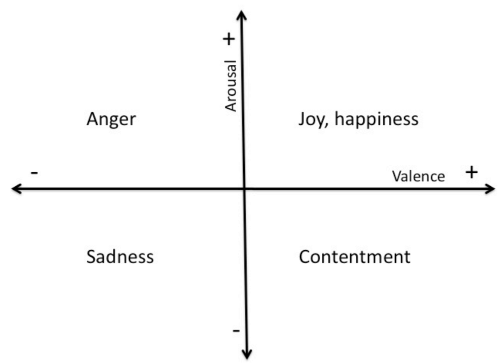


Figure 16 - Discrete affect based on the dimensions valence and arousal.

Based on the two-dimensional emotion model, there are four discrete affect programs (e.g., Feldman, 1995; Gerber et al., 2008): anger, joy, sadness, and contentment (see Figure 16). As discrete affect, such as disgust, surprise, guilt, pride, etc., cannot be mapped in this model without knowledge of the cognitive content of affect, it is focused on the four depicted affect programs (Pfister & Böhm, 2008). Until now, it has not been known how these four discrete affect programs impact on preference decision-making, and especially joy and contentment have not yet been well explored. Nevertheless, research suggests that anger should result in heuristic, and sadness in systematic processing (Tiedens & Linton, 2001). Furthermore, joy should increase the reliance on general knowledge structures without a reduction of processing motivation (Bless et al., 1996). As far as contentment is concerned, no theoretical or empirical basis for a hypothesis is known to the author. Thus, another explorative research question is formulated here with the aim of shedding light on the impact of the four discrete affect programs in the process of preference decision-making.

Explorative research question 2: How do the four discrete affect programs, namely anger, sadness, joy, and contentment, impact consumer choice in DCEs?

This deeper look at discrete affect in consumer choice will serve as an explorative approach to probable constructive processes, especially when experiencing anger or sadness (Tiedens & Linton, 2001).

The review of the theoretical background of this work gives many cues for meaningful cognitive and affective processes during preference decision-making that might be indicative for constructive processes during consumer choice. The reliable measurement of psychophysiological preference-construction indicators might thus allow for a more nuanced understanding of consumer choice, and an improved forecasting of consumers' needs.

6.3 Empirical investigation of affective valence and arousal in consumer choice

The analysis of affect during preference decisions (chapters 4 and 5) focused on specific effects of either higher or lower valence or arousal. The following exploration takes a closer look at the general impact of valence, arousal, both together, and discrete affect on decision-making. Contrary to the previous analyses, the general impacts of valence and arousal on preference expression are of interest here, and not the impacts of either high or low valence / arousal.

6.3.1 Recap Methods

This subsection is a recap, as the study to collect the data is identical to those presented in chapters 4 and 5. The recapitulation of the methods will be convenient for the reader and enable better comprehension.

Some forty-nine students of the University of Hamburg who responded to posted flyers or email invitations participated in this laboratory study for an hourly wage of 10 EUR. Participants were fluent in German, healthy, and were not taking any medication that might affect affective functioning (e.g. antidepressants). Some 53.1% (n = 26) were female. The mean age of the participants was 24.8 (SD = 3.5). Three sets of stimuli were used in three discrete choice experiments (Louviere & Woodworth, 1983) to increase the generalizability of the results: charity, face, and yogurt options. All three stimuli types were described by three attributes with two levels each (see Table 25; see Appendix D for the full set of options).

Table 25 - Attributes and attribute levels for charity, face, and yogurt stimuli.

	Stimulus 1: Charity options	Attribute levels	
Attributes	Living conditions	Bad	Moderate
	Family size	6 people	3 people
	Willingness to learn	Low	Average
	Stimulus 2: Face options	Attribute levels	
Attributes	Eyes	Small	Big
	Nose	Small	Big
	Mouth	Small	Big
	Stimulus 3: Yogurt options	Attribute levels	
Attributes	Fat content	1.5%	3.5%
	Taste	Apricot	Strawberry
	Label	Best standard	Organic

The full-factorial combination of attributes and attribute levels produces a 2 x 2 x 2 factorial or eight option descriptions per stimulus type. These eight alternatives were assigned to 12 choice sets, each with two options. The choice set design is orthogonal and balanced, as suggested by Street and Burgess (2004).

Participants were asked for certain exclusion criteria that could disturb the psychophysiological measurement of affect (particular medications, alcohol, nicotine abuse, caffeine abuse, etc., were not allowed), and demographic questions. Participants were asked to sit in a comfortable chair in an attenuated and dimly lit room. Instructions and stimuli were presented on a 17'' monitor placed approximately 70 cm in front of participants. As arousal was measured with skin conductance response (SCR, Boucsein, 1992), the physiological recording equipment was attached to each subject's non-dominant hand (Fowles et al., 1981). The measurement of affect was conducted via fEMG (Larsen et al., 2003); fEMG surface electrodes were attached on the left side of each subject's face (Rinn, 1984).

Following the setup, the experimental procedure lasted approximately 50 minutes. A computer program presented instructions and choice sets to the participants (Presentation, Neurobs Inc.). Synchronized event markers were used to align SCR data, fEMG data and behavioral choices (indicated by the press of a button). Participants received a short instruction that included practice on how to use the choice buttons, the stimulus presentation, and the attributes and attribute levels of each stimulus type. A 2-second fixation-cross was presented to align initial visual attention and baseline-correction of SCR measures.

Choice sets were presented without time limit, with each presentation ending with choice (button press). After each choice, respondents received a 10-second rest period to regain an affective baseline, and then they progressed at their own pace. Figure 17 shows the course of action in a choice set.

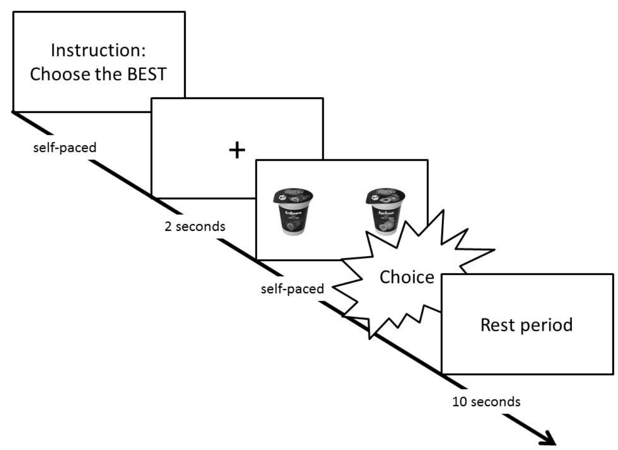


Figure 17 - Course of a choice set with SCR measurement.

The presentation of the three discrete choice experiments started with the face options, followed by the charity options, and ended with the yogurt options. Between the three DCEs, control questions, and stimulus-accordant hold out tasks were presented (four options that had to be ranked by preference). During the DCEs, arousal was measured with skin conductance response, and valence was measured with facial electromyography.

6.3.1.1 Measurement of valence and arousal

SCR is a specific type of measurement of electrodermal activity (EDA) in response to an event (e.g., an object appearing on a screen). EDA is now commonly used and accepted as a measure of arousal with the amplitude of conductance responses serving as an arousal index (Blascovich et al., 1993). The arousal dimension is independent of the approach / avoidance dimension and is ably captured with EDA recordings (Öhman et al., 1993).

The SCR measurement was taken from the non-dominant hand due to the comparability of the thickness of the cornea (hard skin) between individuals. SCR was recorded at the skin surface of participants using SCR100c 8 mm electrodes with electrode gel and amplified using a V-AMP amplifier by BrainProducts. A bipolar placement of the electrodes was used on the thenar and hypo-thenar areas of the palm. The EDA electrode sites were abraded with abrasive paste and isopropyl alcohol pads prior to the placement of the electrodes. A constant voltage procedure passing a 1 Hz signal between the two electrode sites was used to render conductance-related changes due to dermal response to stimulus presentation. The gain on the V-AMP amplifier was set at 5 mS/V. Baseline-corrected SCR magnitudes were standardized within each participant, because the magnitude of skin conductance data can vary between participants not only due to psychological but also physiological causes, such as the thickness of the cornea, and standardization can eliminate or reduce the influence of the latter source of variance (Boucsein, 1992; Dawson et al., 2007).

Measurement of immediate affect via facial electromyography is an established method and has proved reliable in various task contexts (e.g., J. T. Larsen et al., 2003). Facial EMG was recorded in a bipolar fashion (for common-mode rejection, i.e., rejection of interfering muscle signals) over corrugator supercilii (frown muscle) and zygomaticus major (smile muscle) on the left side of the face with 8 mm standard silver / silver-chloride electrodes. Implicit reference and ground electrodes were placed mid-forehead below the hairline.

fEMG signals were relayed through a cable to the V-AMP amplifier (BrainProducts), where signals were amplified. Signals were digitized at 2000 Hz, then recorded and displayed on a laboratory computer. Offline, data was submitted to a 20 Hz high-pass filter and a 500 Hz low-pass filter (van Boxtel, 2010) to reduce movement and blink-related artifacts, then fully rectified. Baseline-corrected fEMG peak-values were used for further analysis due to varying decision durations. The fEMG data was log-transformed prior to statistical (regression) analysis.

6.3.1.2 Data

In total, 588 choices from 49 participants (49 participants x 12 choices) were observed in each stimulus type (charity, faces, yogurts). In order to test the explorative research question 1, which is concerned with the impacts of valence and arousal on preference decision-making, both valence (smile and frown muscle) and arousal measures (skin conductance) were integrated into the latent class analysis of discrete choices as additional choice invariant covariates (Vermunt & Magidson, 2005). To test the joint impact of valence and arousal, a compensatory index (no valence leads to any arousal, vice versa) was calculated.

To test the explorative research question 2, in respect to the impact of discrete affect in preference decision-making, variables indicating the four suggested discrete affect programs (anger, joy, sadness, and contentment) were calculated on the basis of the smile muscle, frown muscle, and skin conductance measures. High or low values of the particular measures were determined on behalf of the individual median values of the respective measure. Figure 18 depicts the ratio of discrete affect inference.

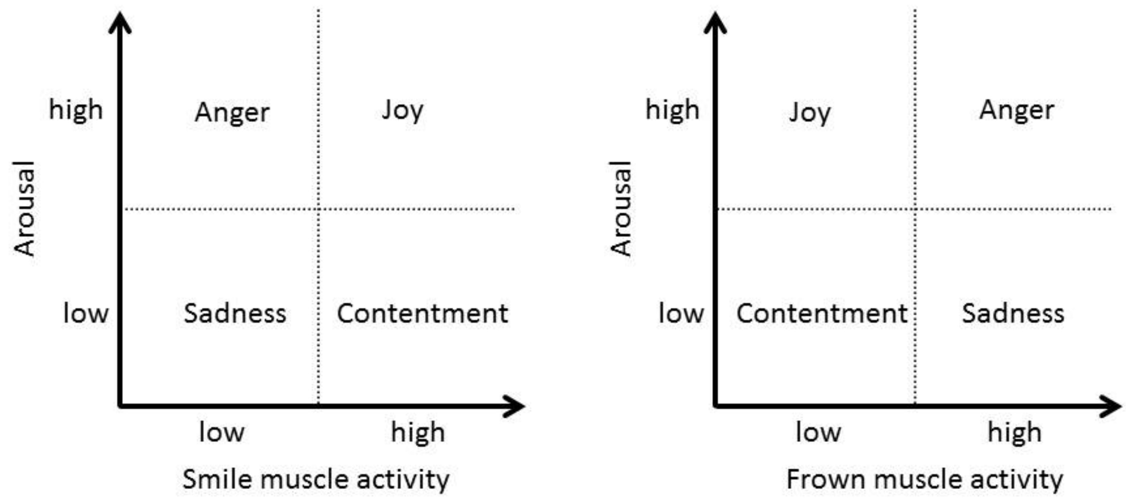


Figure 18 - Inference of discrete affect programs based on smile muscle, frown muscle, and skin conductance measures.

6.3.2 Results

With regard to the first explorative research question, choice models with additional choice invariant covariates for valence (smile / frown muscle activity) and arousal (skin conductance response) are compared with a baseline model without additional parameters. Probable heterogeneity in respect to the interplay of preference and affect is controlled with a latent class analysis, as not only taste can vary from one individual to the next, but also their affective patterns (Oliver & Westbrook, 1993). Owing to the small sample size of this study (n = 49), the consideration of heterogeneity is limited to a maximum of two latent classes, as the degrees of freedom shrink to df = 34 in a two-class model with seven parameters that are to be estimated. Thus, the consideration of more than two latent classes does not make sense in a sample as small as this one. Furthermore, results are considered to be explorative, as the additional consideration of heterogeneity already limits their validity.

For the sake of convenience, only choice models with significant valence, arousal or valence-arousal parameters are explicated. See Appendix E for choice models with non-significant valence, arousal, and valence-arousal parameters. Table 26 presents an overview of estimated latent-class models and respective significant parameters.

Table 26 - Overview of estimated latent class choice models with added valence, arousal, and valence-arousal parameters.

Added parameters	Charity decisions	Face decisions	Yogurt decisions
Smile activity	n.s.	n.s.	Class 2, p = .045
Frown activity	n.s.	n.s.	n.s.
Arousal	n.s.	n.s.	n.s.
Smile X Arousal	n.s.	Class 2, p = .046	n.s.
Frown X Arousal	n.s.	n.s.	n.s.

n.s. = not significant

Only two parameters of valence /arousal seem meaningful in latent class choice models for face and yogurt decisions. For charity decisions, no valence / arousal parameters are significant.

For face decisions, the interaction between smile muscle activity and arousal significantly impacts preference decision-making (see Table 27, class two). The class sizes between the basic two-class model and the two-class model with an additional smile x arousal parameter are approximately the same. Accordingly, parameter estimates of the first classes of both choice models comply with each other. This leads to the notion that heterogeneity based on valence and arousal especially affected the generation of the second latent class. The model with an additional smile x arousal parameter shows a higher BIC value due to the additional parameter. Internal validity indicated by adjusted pseudo-R^2 suggests that class two, with a significant smile x arousal parameter, performs meaningfully better than the respective class two of the basic model. The same can be observed for the predictive validity; the valence-arousal class explains 4% more of the holdout ranks compared with those of class two of the basic model. This is further supported by significantly different utility parameters of the basic class two model, and the valence-arousal class two model.

Table 27 - Latent class choice models with and without valence-arousal parameter in face decisions.

	Without additional par.				With additional smile x arousal par.			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.59		0.41		0.62		0.38	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.18	0.20	-0.18	0.20	0.26	0.22	-0.26	0.22
Eyes – small	**-0.51*** **	0.09	-0.17	0.15	**-0.48*** **	0.08	-0.16	0.20
Eyes – big	**0.51*** **		0.17		**0.48*** **		0.16	
Nose – small	**0.36*** **	0.08	0.12	0.13	**0.38*** **	0.08	0.02	0.17
Nose – big	**-0.36*** **		-0.12		**-0.38*** **		-0.02	
Mouth – small	**0.39*** **	0.12	**-0.77*** **	0.17	**0.34* **	0.12	**-0.92** **	0.28
Mouth – big	**-0.39*** **		**0.77*** **		**-0.34* **		**0.92** **	
Eyes X Nose – diff.	**-0.17** **	0.08	**-0.31* **	0.14	**-0.17* **	0.07	-0.46	0.25
Eyes X Nose – same	**0.17** **		**0.31* **		**0.17* **		0.46	
Eyes X Mouth – diff.	-0.13	0.08	**-0.27* **	0.11	-0.12	0.07	**-0.35* **	0.15
Eyes X Mouth –same	0.13		**0.27* **		0.12		**0.35* **	
Nose X Mouth – diff.	**0.17** **	0.08	**0.36** **	0.10	0.17	0.08	**0.37** **	0.11
Nose X Mouth – same	**-0.17** **		**-0.36** **		-0.17		**-0.37** **	
Smile X Arousal					0.01	0.05	**0.22* **	0.10
Statistics								
Nobs	588				588			
No. of parameters	13				15			
LN likelihood	-338.97				-336.32			
BIC	728.55				731.02			
Adj. pseudo-R2(0)	0.23		0.36		0.22		0.40	
Holdout prediction	0.09		0.28		0.08		0.32	

(*** = p < .001; ** = p < .01; * = p < .05)

For yogurt decisions, only smile muscle activity exerts a significant influence on preference decisions. Yet, besides a slight raise in internal validity, the comparable two-class choice models (see class sizes and parameters) show no further differences (see Table 28).

Taken together, the impacts of valence, arousal, and valence and arousal on preference decision-making are low overall. Nevertheless, the interaction of valence and arousal (smile x arousal in face decisions) shows a higher meaningful impact than valence or arousal (no meaningful impact) alone.

Table 28 - Latent class choice models with and without smile parameter in yogurt decisions.

	Without additional par.				With additional smile par.			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.58		0.42		0.58		0.42	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.14	0.15	-0.14	0.15	0.16	0.16	-0.16	0.16
Taste – apricot	**-0.68*** **	0.10	**0.51*** **	0.17	**-0.67*** **	0.10	**0.58*** **	0.20
Taste – strawberry	**0.68*** **		**-0.51*** **		**0.67*** **		**-0.58*** **	
Fat content – 1.5%	**0.50*** **	0.12	**-0.61*** **	0.13	**0.49*** **	0.12	**-0.66*** **	0.16
Fat content – 3.5%	**-0.50*** **		**0.61*** **		**-0.49*** **		**0.66*** **	
Label – best standard	**-0.47*** **	0.10	**-0.82*** **	0.16	**-0.47*** **	0.09	**-0.87*** **	0.18
Label – organic	**0.47*** **		**0.82*** **		**0.47*** **		**0.87*** **	
Taste X Fat content – diff.	-0.09	0.08	-0.03	0.13	-0.09	0.08	-0.08	0.15
Taste X Fat content – same	0.09		0.03		0.09		0.08	
Taste X Label – diff.	0.01	0.08	-0.06	0.13	0.01	0.08	-0.08	0.15
Taste X Label – same	-0.01		0.06		-0.01		0.08	
Fat content X Label – diff.	-0.01	0.08	0.07	0.13	-0.02	0.09	0.09	0.15
Fat content X Label – same	0.01		-0.07		0.02		-0.09	
Smile					0.12	0.07	**0.20***	0.10
Statistics								
Nobs	588				588			
No. of parameters	13				15			
LN likelihood	-314.78				-310.62			
BIC	680.15				679.62			
Adj. pseudo-R2(0)	0.33		0.39		0.33		0.41	
Holdout prediction	0.50		0.57		0.50		0.57	

(*** = p < .001; ** = p < .01; * = p < .05)

The explorative latent class analysis of discrete affect suggests that sadness, either based on frown or on smile muscle activity, is especially important for preference decision-making. For yogurts, sadness and contentment exert a meaningful influence, for faces only sadness, and for charity decisions discrete affect does not seem to play a role (see Table 29). See Appendix F for choice models with non-significant discrete affect parameters.

Table 29 - Overview of estimated latent class choice models with added discrete affect parameters.

Added parameters	Charity decisions	Face decisions	Yogurt decisions
Discrete affect based on smile activity	n.s.	Class 1 – Sadness, $p = .01$	Class 2 – Sadness, $p < .001$ / contentment, $p = .003$
Discrete affect based on frown activity	n.s.	Class 1 – Sadness, $p = .045$	n.s.

n.s. = not significant

Latent class analysis with additional discrete affect parameters based on the smile muscle activity lead to class sizes that differ significantly, which indicates the interplay of taste and affective patterns. This is not the case for discrete affect based on frown muscle activity (see Table 30). The model with discrete affect based on smile muscle activity exerts a significant influence that is observable in meaningful changes of utility parameters (compared with the baseline model), and thus improvements of internal and predictive validity in class one with the significant sadness parameter. Sadness based on frown muscle activity does not interact with taste patterns, which can be inferred on the comparable class sizes with the basic model. Yet, internal validity (indicated by adjusted pseudo-R^2) rises in class one with the significant sadness parameter (see Table 30).

Table 30 - Latent class choice models with and without discrete affect parameters based on arousal, smile, and frown muscle activity in face decisions.

	Behavioral				Discrete affect based on smile				Discrete affect based on frown			
	Class 1		Class 2		Class 1		Class 2		Class 1		Class 2	
Class size	0.59		0.41		0.64		0.35		0.54		0.45	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.18	0.20	-0.18	0.20	0.30	0.17	-0.30	0.17	0.09	0.21	-0.09	0.21
Eyes – small	**-0.51*** **	0.09	-0.17	0.15	**-0.27** **	0.08	**-0.63*** **	0.14	**-0.53*** **		-0.20	0.13
Eyes – big	**0.51*** **		0.17		**0.27** **		**0.63*** **		**0.53*** **		0.20	
Nose – small	**0.36*** **	0.08	0.12	0.13	**0.21** **	0.08	0.26	0.14	**0.34** **	0.11	0.12	0.12
Nose – big	**-0.36*** **		-0.12		**-0.21** **		-0.26		**-0.34** **		-0.12	
Mouth – small	**0.39*** **	0.12	**-0.77*** **	0.17	**-0.49*** **	0.10	**0.64*** **	0.15	**0.45** **	0.13	**-0.75** **	0.19
Mouth – big	**-0.39*** **		**0.77*** **		**0.49*** **		**-0.64*** **		**-0.45** **		**0.75** **	
Eyes X Nose – diff.	**-0.17** **	0.08	**-0.31***	0.14	**-0.23** **	0.08	-0.09	0.13	**-0.17***	0.09	**-0.26***	0.11
Eyes X Nose – same	**0.17** **		**0.31***		**0.23** **		0.09		**0.17***		**0.26***	
Eyes X Mouth – diff.	-0.13	0.08	**-0.27***	0.11	-0.14	0.09	-0.04	0.13	-0.08	0.10	-0.19	0.13
Eyes X Mouth – same	0.13		**0.27***		0.14		0.04		0.08		0.19	
Nose X Mouth – diff.	**0.17** **	0.08	**0.36** **	0.10	**0.28** **	0.07	0.12	0.12	**0.18***	0.09	**0.35** **	0.10
Nose X Mouth – same	**-0.17** **		**-0.36** **		**-0.28** **		-0.12		**-0.18***		**-0.35** **	
Anger					0.06	0.07	0.01	0.11	0.02	0.07	0.04	0.11
Joy					0.08	0.07	0.15	0.10	0.04	0.07	0.01	0.09
Sadness					**0.21** **	0.07	0.13	0.11	**0.16***	0.08	0.06	0.09
Contentment					0.01	0.07	0.11	0.10	0.13	0.08	0.12	0.10
Statistics												
Nobs	588				588				588			
No. of parameters	13				21				21			
LN likelihood	-338.97				-334.87				-333.76			
BIC	728.55				751.48				749.24			
Adj. pseudo-R^2(0)	0.23		0.36		0.26		0.36		0.27		0.34	
Holdout prediction	0.09		0.28		0.15		0.18		0.08		0.24	

(*** = p < .001; ** = p < .01; * = p < .05)

For yogurt decisions, two discrete affect programs - sadness and contentment - have a significant impact on preference decision-making. The differing class sizes of the basic and the discrete affect model indicate that the heterogeneity is based on taste and affective patterns. The rather small class two of the discrete affect model suggests a significant improvement of internal and predictive validity due to the joint consideration of heterogeneity and discrete affect (see Table 31).

Table 31 - Latent class choice models with and without discrete affect parameters based on arousal and smile muscle activity in yogurt decisions.

	Behavioral				Discrete affect based on smile			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.58		0.42		0.71		0.29	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.14	0.15	-0.14	0.15	**0.46****	0.16	**-0.46****	0.16
Taste – apricot	**-0.68*****	0.10	**0.51*****	0.17	**-0.41*****	0.07	**1.46****	0.57
Taste – strawberry	**0.68*****		**-0.51*****		**0.41*****		**-1.46****	
Fat content – 1.5%	**0.50*****	0.12	**-0.61*****	0.13	**0.37*****	0.08	**-2.45****	0.70
Fat content – 3.5%	**-0.50*****		**0.61*****		**-0.37*****		**2.45****	
Label – best standard	**-0.47*****	0.10	**-0.82*****	0.16	**-0.49*****	0.08	**-2.04****	0.63
Label – organic	**0.47*****		**0.82*****		**0.49*****		**2.04****	
Taste X Fat content – diff.	-0.09	0.08	-0.03	0.13	-0.07	0.07	-0.22	0.54
Taste X Fat content – same	0.09		0.03		0.07		0.22	
Taste X Label – diff.	0.01	0.08	-0.06	0.13	-0.01	0.08	-0.06	0.57
Taste X Label – same	-0.01		0.06		0.01		0.06	
Fat content X Label – diff.	-0.01	0.08	0.07	0.13	0.01	0.07	0.56	0.54
Fat content X Label – same	0.01		-0.07		-0.01		-0.56	
Anger					0.05	0.06	0.24	0.19
Joy					0.04	0.06	0.38	0.21
Sadness					0.04	0.06	**0.59*****	0.16
Contentment					0.01	0.06	**0.76****	0.22
Statistics								
Nobs	588				588			
No. of parameters	13				21			
LN likelihood	-314.78				-303.42			
BIC	680.15				688.58			
Adj. pseudo-R2(0)	0.33		0.39		0.25		0.67	
Holdout prediction	0.50		0.57		0.50		0.60	

(*** = p < .001; ** = p < .01; * = p < .05)

In short, sadness in particular as a discrete affect program has an impact on preference decision-making. Results indicate that consideration of heterogeneity in respect of taste and affective patterns reveals the potential of the integration of discrete affect in DCE analysis.

6.4 Discussion and outlook of valence and arousal in consumer decision-making

Valence and arousal are thought to play an essential role in the evaluation of options during decision-making (Peters, 2006). This point is empirically supported in a study of Suri et al. (2013) in which IAPS pictures (Lang, Bradley, & Cuthbert, 1999) were rated on subjective rating scales. This present study goes above and beyond this approach by using non-obtrusive psychophysiological measures as indicators for valence (fEMG) and arousal (SCR) in consumerlike preference decisions (DCEs).

Comparable to the results of Suri et al. (2013), the results of this study suggest that valence and arousal can explain more variance in preference decision-making than valence or arousal alone. As valence and arousal considered jointly have a higher impact on preference than considered separately, it is suggested that both together determine approach and avoidance (Watson, Wiede, Vaidya, & Tellegen, 1999), and not valence alone (e.g., Elster, 1998, Bower, 1991).

Yet, this result depends on several factors that have to be considered. First of all, not all stimuli-types in use (charity, faces, and yogurts) exert the same significant parameters. Second, the smile muscle activity, also in combination with arousal, is more indicative than the frown muscle activity. The results hint at the feasibility of psychophysiological valence and arousal measures, and also at their comparability to results with subjective measures (Suri et al., 2013). Nonetheless, many non-significant analyses also suggest the necessity to consider more noise-producing factors when using psychophysiological indicators of valence and arousal (Wang & Minor, 2008).

However, the results point to the importance of valence and arousal, also in consumerlike preference decisions. To a small but encouraging degree, the inclusion of additional affective processes explains more variance (internal validity) and also more about subsequent decision-making (predictive validity), as in the case of class two in face decisions. Thus, owing to the inclusion of valence and arousal, the construction of preference can be captured to some point. This finding might be based on the functional role of affect during decision-making as common currency (Peters, 2006). Valence and arousal provide the boundaries between which decisions should be made, as affect supplies an abstract scale of preference for otherwise incomparable evaluations.

This evidence is further underpinned by the results concerned with discrete affect in preference decision-making. Several researchers suggested that discrete affect programs, and not valence or arousal alone, impinge on decision-relevant processes (e.g., Lowenstein & Lerner, 2003; Tiedens & Linton, 2001). The results of this study support previous research and show that sadness in particular, the negative counterpart of anger, impacts preference decision-making. In line with Tiedens and Linton (2001), the small but inspiring rise in internal and predictive validity due to the inclusion of a sadness parameter can be attributed to more systematic processing when individuals are sad. Of course, the stimuli in this study did not induce severe sadness but rather a subtle passive avoidance motivation.

Again, the use of psychophysiological indicators for discrete affect make it necessary to consider various factors, as results are not the same for all types of stimuli. The results suggest that the smile muscle seems to be a better affect indicator than the frown muscle, and subjects show not only preferentially but also affectively heterogenic patterns (Oliver & Westbrook, 1993).

A central limitation of the approach in this study is the conflation of preference heterogeneity and affective heterogeneity in the generation of latent classes. Thus, future studies should be aware of possible heterogeneity in affective patterns and induce affect experimentally in order to reduce probable heterogeneity (Westermann, Spies, Stahl, & Hesse, 1996). The experimental induction of affect would also allow inducing affect programs that are probably not induced by classic DCE stimuli but could be relevant for real-world decisions, such as anger, for example.

This explorative study showed that psychophysiological methods are applicable to scrutinize the role of affect in decision-making, even when discrete affect is inferred on their basis. Furthermore, the joint exploration of valence and arousal reveals untapped potential in order to improve analysis and prediction of preference with DCEs. Thus, future researchers are encouraged to use immediate affect measures to further explore relevant cognitive and affective processes during preference decision-making.

7 General discussion

All the analyses presented in this work are based on psychophysiological indicators for cognitive and affective processes during preference decisions in DCEs. The results of the studies concerned with visual attention, valence, and arousal in DCEs substantiate the use of psychophysiological indicators for preference research (see also Reid & Gonzales-Vallejo, 2009). Psychophysiology allowed an additional view on consumers' cognitive and affective mechanisms. The otherwise either unobservable, or unreliably observable impacts of information processing and affect (e.g., Wiles & Cornwell, 1991) on preference decision-making yielded potentially valuable insights into the process of preference decision-making.

7.1 Consolidation of results

Regarding visual attention as an indicator for information processing during preference decisions, the well-known quote of Pieters and Warlop (1999, p. 14), "choice can be predicted from observations of visual patterns only," could not be confirmed. However, a finer-grained analysis of visual attention, which considered the time course of preference decision-making, revealed that a certain kind of information processing indicates more stable preferences in the short term and the long term. An early gaze bias on the later choice, followed by a focus on disliked options, indicates an error-prone decision process. A correction of the behaviorally expressed choice in this process into a choice that follows an initial elimination by aspects and a final verification outperforms the behavioral model for internal and predictive validity. Thus, the analysis of information processing provides additional valuable insights into its role during preference decisions.

The integration of valence in models of choice revealed meaningful impacts of positive or negative valence on preference decision-making. Depending on the stimulus-induced task demand the subjects had to operate with, results indicate that valence measured with facial electromyography acts as a marker that flags value (somatic marker, Bechara & Damsio, 2005), as well as a possible indicator for information-processing styles (e.g., Schwarz & Clore, 1996). The integration of positive and negative valence leads to an improvement of the short-term and longer-term stability of preference expression, and thus can be seen as a means to control for constructive processes during preference expression.

Choice models with higher and lower affective arousal uncovered the multifaceted functions of the seemingly trivial arousal construct (Boucsein, 2012). Based on results of this study, arousal can be considered a somatic marker (Bechara & Damsio, 2005), as well as an indicator for complexity reduction (Paulhus & Lim, 1994), and an indicator for optimal information processing during decision-making (e.g., Kaufman, 1999). Although future researchers are encouraged to explore the antecedents and contingencies of the different functions of arousal, it is clear that arousal does have the potential to indicate eventually constructive processes during preference decision-making.

The combined explorative consideration of valence and arousal, and also discrete affect, reveal that these basic dimensions of affective experience (Mehrabian, 1996) jointly interact with preference decision-making. Interestingly, sadness, as a discrete counterpart of anger, leads to improved short-term and long-term stability of preference. The reason for this might be the more systematical decision-making induced by sad mood (Tiedens & Linton, 2001). Although the interplay of preference and affective heterogeneity is an issue to be tackled in future analyses (Oliver & Westbrook, 1993), the results of this study denote the potential of discrete affect in DCEs for identifying preference construction. The short- and long-term stability of preference elicitation should increase when discrete affect during decision-making is integrated in the analysis and prediction of choice (see also Araña, León, & Hanemann, 2008). Furthermore, the consideration of affect in DCEs could yield new affect-based contact points for innovative marketing actions (e.g., product development, advertisement). The results in this study may very well be founded on elementary memory processes; consequently, these processes are discussed in the following section in the light of the results that were achieved.

7.2 Memory processes as source of preference construction

The expression of preference can be conceptualized as the result of the memory system, as knowledge related to preferences should possess the same properties as other types of knowledge (Weber & Johnson, 2009). By using psychophysiological indicators, basic memory processes as a source of information processing could be identified. Thus, psychophysiological measures helped to conceptualize decision-making as a product of memory processes and allowed the identification of deviations from the rational choice modeling approach.

For the study of visual attention during preference decision, the accessibility of memory in particular is crucial. As the study of visual attention did not experimentally manipulate the accessibility by priming, for example (Bargh, Chen, & Burrows, 1996), a kind of self-induced priming is assumed. As subjects have to follow a sequential order of information processing during decision-making, they get primed by the order of informational input (Russo, Meloy, & Wilks, 2000). The analysis of the process of visual attention during preference decision in this study underpins and extends these findings, as a certain process (first look at the option that was chosen later, then at the one that was not) presumably indicates erroneous self-priming and eventually leads to inconsistent preference expressions. The correction of this primed preference results in higher internal and predictive validity compared with the purely behavioral choice model.

This also indicates that the order of how preference decisions are made plays an important role consumer choice (Johnson, Haubl, & Keinan, 2007). When individuals first ask themselves what they don't like (EBA) and subsequently ask themselves what they do like (verification), decisions become more consistent as opposed to what happens in the opposite sequence of inquiry. The opposite code of conduct (first like, then dislike) could lead to a suppression of reasons to like an option (Koriat, Lichtenstein, & Fischhoff, 1980) and eventually to overconfidence, and biased choice expression. Thus, the integration of visual attention in the analysis of choice also provides a deeper understanding of the memory processes during preference decisions.

Further insight into the role of visual attention during preference decisions can be obtained by a comparison of bottom-up and top-down effects (e.g., Towal, Mormann, & Koch, 2013). A review of visual attention in decision research by Orqiun and Müller-Loose (2013) showed that visual attention during decision-making is not only driven by information demands but also by stimulus-induced processes, and interactions with working memory. They suggest that the eventual choice is not a simple product of preference but a complex interaction between stimulus-induced and memory-induced processes. That attention plays a constructive role in decision-making is also supported by results of Towal, Mormann, and Koch (2013). They compared models of visual attention during choice that are based only on saliency, only on value, or on both saliency and value. The model with combined saliency and value parameters outperformed the other models and suggested that one-third of value is dependent on saliency, and two-thirds are dependent on actual preference. The future challenge will lie in the applicability of this approach for preference elicitation (one possible approach is presented in this study), and of course, a further refinement of the theoretical and empirical bases for the interaction between visual attention and memory processes.

The concept of somatic markers, which indicate memory accessibility, dominates the research of valence and arousal in decision-making (Bechara & Damsio, 2005, Sherman & Kim, 2002). This is also true for this study, as affect and arousal indicate the existence of prior experience with the options. Prior experience with options presumably leads to higher memory accessibility, and thus to a higher consistency of preference expression. Besides indicating the (non-)existence of somatic markers, affect can also impact the accessibility of memory due to information-processing aspects (Schwarz & Clore, 1996). The results of this study suggest that negative affect could have led to relatively low predictive validity of preference elicitation, because reliance on pre-existing memory content was low (in line with Loewenstein & Lerner, 2003).

Not only do the predominant concepts of somatic markers and memory accessibility play an important role in decision-making, but so does affect-indicated memory interference. Arousal, for example, could indicate the development of somatic markers, or the re-structuring of already existing somatic markers, and thus memory interference. The latter case is presumed to lead to inconsistent preference expressions, whereas the former should lead to consistent preference expressions. This interpretation of the present finding for arousal would also be in line with the notion that memory is always changed when it is accessed (e.g., Chapman & Johnson, 1999). More recent research by Davis, Love, and Maddox (2009) further substantiates the alterable role of affect and suggests that affect can act both as input (as a somatic marker), and as an output (as preparatory action). In the first case, affect "act[s] as covert biases on the circuits that support processes of cognitive evaluation" (Bechara et al., 1997, p. 1294), whereas in the latter case, affect is assumed to enhance the ability to learn when people's memory representations are inadequate to cope with the particular problem (Love & Gureckis, 2007; Yu & Dayan, 2005).

Comparable to the order of information processing that is retrievable by visual attention in preference decision-making; the order of affect during preference decisions could make a meaningful difference. Until now, only the temporal effects of the retrospective evaluation of a decision has been explored (Ritov, 2006), but not the time course of immediate affect during decision-making. As affect leads to more or less accessibility of the respective memory content, the order of affect could lead to a self-induced affective priming (Winkielman, Schwarz, Fazendeiro, & Reber, 2003). For example, when a respondent feels sad at the beginning of the evaluation but then experiences joy, information gathered at the time of the sad mood could interfere with information gathered in the joyful mood, and thus the impact of sad mood could be overestimated.

Another important aspect of immediate affect during decision-making is the differentiation between integral and incidental affect during decision-making and its impacts on memory processes. Whereas integral affect is associated with the relevant decision problem, incidental affect is not related to the decision problem (Loewenstein & Lerner, 2003). It is assumed that integral affect should lead to specific memory effects (e.g., inhibition of certain information types), whereas incidental affect should lead to unspecific memory effects (e.g., a certain processing style).

The presented studies are the first approach to measure, analyze and interpret visual attention and immediate affect in a preference elicitation context. Thus, they are also the first approach to combine behavioral outcomes (choices) and psychophysiological processes (its antecedents) within a workable preference elicitation paradigm (as suggested by Johnson, Schulte-Mecklenbeck, & Willemsen, 2008).

Especially the “hot” affect (immediate affect), and not the “cold” affect (anticipatory affect), has received and will receive growing attention in decision research (Peters, Vastfjall, Gärling, & Slovic, 2006). The focus on “hot” affect is substantiated by several studies showing that anticipated affect does not explain actual decision behavior (Ariely & Loewenstein, 2006). This study showed that “hot” affect is also relevant in preference decisions within a DCE paradigm, which is systematically set up, and more artificial than real-world decisions. Thus, the present findings are understood as conservative tests of the impacts and functions of affect in preference decisions. It is assumed that affect is much more powerful for real-world decisions, and its probable preference constructive consequences.

7.3 Psychophysiological processes indicate preference construction

Recent research further substantiated that preferences are at least partially constructive (e.g., Simonson, 2008). Reasons for this constructiveness are assumed in the vast number of perceptive, cognitive and affective processes that influence and eventually constitute decision-making (e.g., McFadden, 1999). The presented research addressed this issue and operationalized perceptive, cognitive and affective processes with the help of psychophysiological methods (as already recommended by Kahneman, Wakker, & Sarin, 1997). As suggested by Simonson (2008, p. 164), the conducted studies show that psychological processes can indicate the relative weight of stable or constructed preference in revealed preference. For example, the substitution of behavioral choice with options that followed a certain gaze process (options that are first disliked, then liked) in the study of visual attention in preference decision-making reveals that 45% of behaviorally indicated choices could have been constructed (see Table 2). Furthermore, the meaningful splitting of behavioral choices based on the medians of affect and arousal also suggests that a large part of choices might be prone to constructive processes. Thus, this research points out that it is feasible to disentangle possibly constructed preference expressions and identify eventually stable preference expressions with the utilization of psychophysiological indicators of perceptive, cognitive and affective processes.

On a more abstract level, it is presumed that perception and cognition lead to preference construction (Tversky & Kahneman, 1990; Payne et al., 1992). Hitherto presented research took a more specific focus on these aspects, as visual attention could indicate perception and cognition, and affective processes could indicate cognition (affect is in a sense cognition; see Ledoux, 1989; Panksepp, 2003). Thus, this research cannot infer how much these two processes contribute to the construction of choice. Future research should therefore combine the respective psychophysiological measures (visual attention and affect) in order to disentangle the impacts of these abstract concepts on preference construction. Nonetheless, this research provided valuable insights into the finer-grained perceptive and cognitive processes taking place during expression of probably constructed / stable preferences.

The disentanglement of more or less constructed preference also indicates that simple quasi-linear models (logit models, e.g., Train, 2009) are capable of capturing the process of preference decision-making. Thus, this work shows that "regression models […] conveniently serve as baselines for comparing various process models" (Einhorn, Kleinmuntz, & Kleinmuntz, 1979, p. 482). This also means that standard models of choice in economics are not generally inappropriate to describe and analyze preference decisions. With the support of cognitive and affective process measures, it is feasible to differentiate between choices that follow the assumptions of the standard model in economics and choices that are probably constructed. Stable choices based on psychophysiological measures are therefore consistent, and the according cognitive process is simply utility maximization (McFadden, 1999, p. 75).

A large amount of research concerned with the constructive nature of preference follows the approach to manipulate contextual factors (decoys as alternatives, Huber et al., 1982; task framing, Tversky & Kahneman, 1981, Slovic et al., 2006) in order to gain insights with regard to impact factors. The multitude of contextual factors that eventually lead to preference construction make this approach an exhausting, but nevertheless critical endeavor. By contrast, the research presented here focused on the internal context, i.e., cognition and affect of the decision-maker. This approach allows exploring effects of preference construction without a strict manipulation of the context; of course, context should nevertheless be considered very closely. A focus on the source of preference construction (decision-maker) is not only more practical, as analysis can be adapted to quasi real-world decisions, but moreover, it is suggested that understanding the cognitive and affective processes of the decision-maker can further narrow the gap between economic and behavioral decision theories (Simonson, 2008). As this research has shown, both perspectives deliver important theoretical (BDT, see Slovic et al., 2006) and methodological (DCE, see Louviere & Woodworth, 1983) aspects that provide validity.

This work also points out that the consideration of decision processes is a chance for preference elicitation, as dispositional stable preferences are identifiable, and so are the fast and temporally local modifications of consumers' preferences. The closer look at cognitive and affective processes with psychophysiological methods allowed opening the window to the master list of preferences a little bit wider.

For the interested market practitioner, the possibility to know when and why preference elicitation was stable or constructed should be invaluable. Of course, it is suggested that new product development, for example, should better match the consumers' needs if based on the master list of preference, and not on some locally expressed preferences. Furthermore, when the context of decision-making is considered, the reason for preference construction could also be answered. For example, if certain attributes (e.g., the taste of yogurt) alter in impact-weight when cognitive / affective processes are integrated in the preference elicitation, this attribute could be the source of preference construction. It is also important for consumer communication to know why preferences are constructed, as advertisements, etc., can be created based on that knowledge. Attributes that lead to preference construction should be highlighted to increase the chance that this information be used for decision-making.

To know why and when preferences are likely to be constructed is suggested to be especially crucial in the contexts of fast-moving consumer goods (FMCGs). Regarding FMCGs, consumers tend to spend little mental effort on decision-making (i.e., on autopilot) that sometimes leads to disadvantageously constructed choices (Shiv & Fedorikhin, 1999). Therefore, and given the quite high failure rates of new products, for example (50% or higher; e.g., GfK research, 2006), the implementation of psychophysiological measures as an additional source of information with respect to the constructiveness of expressed preferences could constitute an approach to increase the success rate of new products.

This research is the first approach known to the author that tackles the challenge of integrating real cognitive and affective process-data within a sound preference elicitation method (DCEs) in order to gain a deeper understanding of preference construction. Of course, this is just a first explorative step, and new challenges arose along the way (e.g., affective heterogeneity). Thus, it is recommended that future researchers on this topic focus on the interplay of cognitive / affective and contextual factors. The framing of decisions in either best or worst decision-making is considered fruitful, especially as best-worst scaling is gaining influence in preference elicitation (Flynn et al., 2007). Prior research has shown, that worst decisions led to more consistent preference expression, which hints at less preference construction (Kogut, 2011). In this view, yet related to personal characteristics, the regulatory focus orientation (prevention or promotion) of decision-makers could further influence cognitive and affective processes, and thus the susceptibility to construct preference (see Pham & Higgins, 2005).

This study supports the feasibility of measuring cognitive and affective processes during preference decision-making (as already suggested by Kahneman, Wakker, & Sarin, 1997). Therefore, preference decision researchers are encouraged to continue pursuing this path and deepen the theoretical and methodological understanding of preference elicitation to further open the window to the master list of preference.

Appendix A - Measurement of subjective difficulty, processing style, and pre-knowledge

Difficulty was measured in a bipolar fashion with four items on a five-point Likert-scale (Cronbach’s alpha = .77):

German original: „Die Beurteilung der Attraktivität von <Stimulus-Typ> …”
Translation: “The evaluation of attractiveness of <stimulus-type> was …”

1. German original: „ … war eine Herausforderung vs. … war leicht zu bewerkstelligen“
   Translation: “ … a challenge vs. … without effort“
2. German original: „ … war komplex vs. … war mühelos”
   Translation: “ … complex vs. … without any trouble”
3. German original: „ … fiel mir schwer vs. … fiel mir leicht”
   Translation: “ … difficult for me vs. ... easy for me”
4. German original: „ … bedurfte intensiver Konzentration vs. … bewältigte ich spontan“
   Translation: “ … demanding intensive concentration vs. … relative spontaneous“

Processing style was measured in a bipolar fashion with four items on a five-point Likert-scale (1 = analytic, 5 = holistic; Cronsbach’s alpha = .705).

German original: „Ich beurteilte die <Stimulus-Typ> …”
Translation: „I evaluated <stimulus-type> …”

1. German original: „ … nach Teilbereichen vs. … als Einheit”
   Translation: “ …based on partitions vs. … as entity“
2. German original: „ ... anhand einzelner Partien vs. … über den Gesamteindruck“
   Translation: “ …based on distinct sections vs. …based on overall impression“
3. German original: „ … durch den Vergleich einzelner Merkmale vs. ... durch die Betrachtung des Großen und Ganzen“
   Translation: “ …based on a comparison of single attributes vs. …based on the big picture“

4. German original: „ … nach genauer Betrachtung von Details vs. … auf einen Blick“
   Translation: “ …based on close observation of details vs. … at a glance“

Pre-knowledge was measured with four items on a five-point Likert-Scale (1 = less pre-knowledge, 5 = more pre-knowledge; Cronbach’s alpha = .81). Items are based on the scale developed by Mukherjee and Hoyer (2001).

1. German original: „Im Vergleich zu anderen Personen kenne ich mich mit <Stimulus-Typ> recht gut aus.“
   Translation: “Compared to other people, I know <stimulus-type> quite well.”
2. German original: „Im Vergleich zu anderen Personen mache ich mir viel Gedanken über <Stimulus-Typ> im Allgemeinen.“
   Translation: “Compared to other people, I give a lot of thought to <stimulus-type> in general.”
3. German original: „Ich bin mit den verschiedensten <Stimulus-Typ> vertraut.“
   Translation: “I am familiar with different types of <stimulus-type>.”
4. German original: „Ich habe mich mit der Attraktivität von <Stimulus-Typ> schon oft auseinandergesetzt.“
   Translation: “I often dealt with the attractiveness of <stimulus-type>.”

Appendix B - Measurement and analysis of facial electromyography

Study setup for facial electromyographic (fEMG) measures during consumer choice:

1. Design of choice sets (e.g., four decision options per choice set) and training choice sets (e.g., four affectively neutral pictures per set, taken from IAPS, Lang, Bradley, & Cuthbert, 1999).
2. Implementation of study design in presentation (experimental software, Neurobs Inc.). First, 10 training trials are presented, then experimental trials. Introductions / instructions should be presented before each new stimulus material (faces, charity, and yogurts). Before each choice set, a fixations cross with 2 seconds duration should be shown for the centering of initial visual attention. After each choice set, a stop sign for 10 seconds should be presented as a break between choice tasks (regain emotional baseline).
3. Implementation of markers (port-outputs) in presentation that indicate the progress of the study (marker for every event in the study, f. ex., Marker “S1” for the start of the fixations cross, and “S2” for the end of the fixation cross, etc.). Markers are sent over the LPT (line print terminal) to the amplifier that records the fEMG signals. Markers indicate the relevant segments of analysis (time from start to end of stimulus presentation, i.e. choice duration).

Placement of electrodes – surface preparation

1. Abrasion of facial surface midst forehead below the hairline (position for reference electrodes), above one eyebrow on an imaginary vertical line that traverses the inner commission of the eye fissure (corrugator supercilii, frown muscle), and midway along an imaginary line joining the corner of the mouth and the bony dimple above the posterior edge of the cheek bone (zygomaticus major, smile muscle). Cleaning is important to reduce resistance of the skin, and lower the noise in the fEMG signal.
2. Filling of cup electrodes with a pea sized portion of adhesive conduction paste.
3. Placement of filled silver / silver-chloride electrodes with self-adhesive rings on the three (above described) spots on the face.

Analysis of fEMG data

1. Data recording without any filters (raw data). Data is thus is overlaid with noise producing sources.
2. Filtering of data with a 400 Hz low-pass and a 20 Hz high-pass filter, and a 50 Hz notch filter.
3. Rectification of data for further analysis (otherwise computation of means would result in null).
4. Segmentation of data based on marker-positions.
5. Calculation of absolute difference between two electrodes per muscle. This further cleans out noise from cross-talk from other muscle regions (also called common mode rejection).
6. Calculation of peak-values of every segmented piece of data (i.e., for every choice set).
7. Aggregated data is logarithmized in order to approximate a normal distribution.

Appendix C - Measurement and analysis of skin conductance response

Study setup for skin conductance response (SCR) measures during consumer choice:

1. Design of choice sets (e.g., four decision options per choice set) and training choice sets (e.g., four affectively neutral pictures per set, taken from IAPS, Lang, Bradley, & Cuthbert, 1999).
2. Implementation of study design in presentation (experimental software, Neurobs Inc.). First, 10 training trials were presented, then experimental trials. Introductions / instructions should be presented before each new stimulus material (faces, charity, and yogurts). Before each choice set, a fixations cross with 2 seconds duration should be shown for the centering of initial visual attention. After each choice set, a stop sign for 10 seconds should be presented as a break between choice tasks (regain emotional baseline).
3. Implementation of markers (port-outputs) in presentation that indicate the progress of the study (marker for every event in the study, f. ex., Marker "S1" for the start of the fixations cross, and "S2" for the end of the fixation cross, etc.). Markers are sent over the LPT (line print terminal) to the amplifier that records the SCR signals. Markers indicate the relevant segments of analysis (time from start to end of stimulus presentation).

Placement of electrodes – surface preparation

1. Abrasion of palmar sites, anywhere on thenar (heel of the thumb) and hypothenar (heel of the small finger) sites, on the same non-dominant hand. Cleaning is important to reduce resistance of the skin, and lower noise in the SCR signal.
2. Filling of two cup electrodes (bipolar recording) with a pea sized portion of adhesive conduction paste.
3. Placement of filled silver / silver-chloride electrodes with self-adhesive rings on the two (above described) spots on the palm of the non-dominant hand (less hard skin on the non-dominant hand, and thus less resistance).
4. As skin conductance measures require a constant current flow through the skin, a voltage of 0.5 volt is applied.

Analysis of SCR data

1. Data recording without any filters (raw data). Data is thus is overlaid with noise producing sources.
2. Filtering of data with a 1 Hz low-pass and no high-pass filter.
3. Rectification of data for further analysis (otherwise computation of mean would result in null).
4. Segmentation of data based on marker-positions.
5. Calculation of peak-values of every segmented piece of data (i.e., for every choice set).

Appendix D - Stimulus material for empirical studies

Shoe stimuli for the study of visual attention in preference decision-making (Chapter 3):

Charity stimuli for the study of affect in preference decision-making (chapters 4, 5, and 6):

Familie A	
Lebens-bedingungen	angemessen
Familien-größe	3 Menschen
Lern-bereitschaft	durchschnitt

Familie B	
Lebens-bedingungen	angemessen
Familien-größe	6 Menschen
Lern-bereitschaft	durchschnitt

Familie B	
Lebens-bedingungen	schlecht
Familien-größe	6 Menschen
Lern-bereitschaft	schlecht

Familie A	
Lebens-bedingungen	schlecht
Familien-größe	3 Menschen
Lern-bereitschaft	schlecht

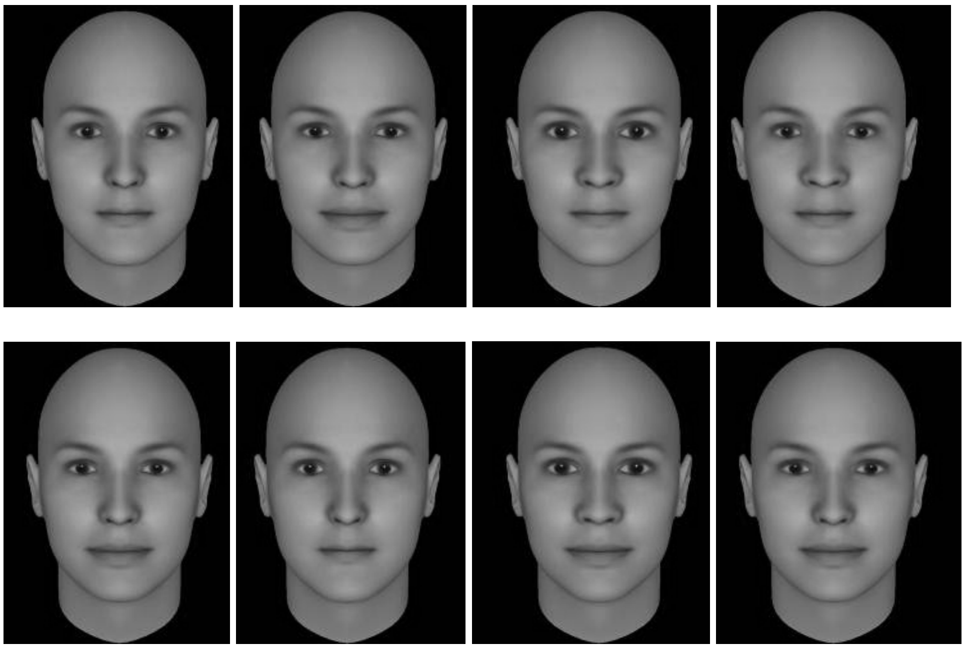
Familie B	
Lebens-bedingungen	schlecht
Familien-größe	3 Menschen
Lern-bereitschaft	durchschnitt

Familie A	
Lebens-bedingungen	angemessen
Familien-größe	6 Menschen
Lern-bereitschaft	schlecht

Familie B	
Lebens-bedingungen	angemessen
Familien-größe	3 Menschen
Lern-bereitschaft	schlecht

Familie A	
Lebens-bedingungen	schlecht
Familien-größe	6 Menschen
Lern-bereitschaft	durchschnitt

Face stimuli for the study of affect in preference decision-making (chapters 4, 5, and 6):



Yogurt stimuli for the study of affect in preference decision-making (chapters 4, 5, and 6):

Appendix E - Latent class choice models with non-significant valence, arousal, or valence-arousal parameters

Tables start on next page due to table size.

Table 32 - Latent class choice models for charity decision with and without additional smile parameter.

	Without additional par.				With additional par.			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.61		0.39		0.61		0.39	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.20	0.16	-0.20	0.16	0.20	0.16	-0.20	0.16
Living cond. – bad	**3.54*** **	1.05	**0.66*** **	0.14	**3.54*** **	1.05	**0.66*** **	0.14
Living cond. – moderate	**-3.54*** **		**-0.66*** **		**-3.54*** **		**-0.66*** **	
Family size – 3	-0.95	0.56	**-0.27***	0.12	-0.96	0.56	**-0.27***	0.12
Family size – 6	0.95		**0.27***		0.96		**0.27***	
Will. learn – avg.	**-1.32***	0.56	**-1.19*** **	0.14	**-1.32***	0.56	**-1.19*** **	0.14
Will. learn – low	**1.32***		**1.19*** **		**1.32***		**1.19*** **	
Living X Family – diff.	0.63	0.56	0.08	0.14	0.63	0.56	0.08	0.14
Living X Family – same	-0.63		-0.08		-0.63		-0.08	
Living X Learn – diff.	0.36	0.56	0.01	0.12	0.35	0.56	0.01	0.12
Living X Learn – same	-0.36		-0.01		-0.35		-0.01	
Family X Learn – diff.	0.23	1.05	0.04	0.12	0.23	1.05	0.04	0.12
Family X Learn – same	-0.23		-0.04		-0.23		-0.04	
Smile parameter					0.11	0.14	0.01	0.10
Statistics								
Nobs	588				588			
No. of parameters	13				15			
LN likelihood	-167.41				-168.49			
BIC	391.24				394.37			
Adj. pseudo-R2(0)	0.82		0.49		0.82		0.49	
Holdout prediction	0.73		0.75		0.73		0.75	

(*** = p < .001; ** = p < .01; * = p < .05)

Table 33 - Latent class choice models for charity decision with and without additional frown parameter.

	Without additional par.				With additional par.			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.61		0.39		0.60		0.40	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.20	0.16	-0.20	0.16	0.19	0.17	-0.19	0.17
Living cond. – bad	**3.54*** **	1.05	**0.66*** **	0.14	**3.66*** **	1.05	**0.68*** **	0.14
Living cond. – moderate	**-3.54*** **		**-0.66*** **		**-3.66*** **		**-0.68*** **	
Family size – 3	-0.95	0.56	**-0.27***	0.12	-0.95	0.56	**-0.27***	0.12
Family size – 6	0.95		**0.27***		0.95		**0.27***	
Will. learn – avg.	**-1.32***	0.56	**-1.19*** **	0.14	**-1.32***	0.56	**-1.20*** **	0.14
Will. learn – low	**1.32***		**1.19*** **		**1.32***		**1.20*** **	
Living X Family – diff.	0.63	0.56	0.08	0.14	0.62	0.56	0.08	0.14
Living X Family – same	-0.63		-0.08		-0.62		-0.08	
Living X Learn – diff.	0.36	0.56	0.01	0.12	0.33	0.56	0.01	0.12
Living X Learn – same	-0.36		-0.01		-0.33		-0.01	
Family X Learn – diff.	0.23	1.05	0.04	0.12	0.27	1.05	0.04	0.12
Family X Learn – same	-0.23		-0.04		-0.27		-0.04	
Frown parameter					0.13	0.13	-0.13	0.10
Statistics								
Nobs	588				588			
No. of parameters	13				15			
LN likelihood	-167.41				-167.40			
BIC	391.24				393.19			
Adj. pseudo-R2(0)	0.82		0.49		0.82		0.50	
Holdout prediction	0.73		0.75		0.73		0.75	

(*** = p < .001; ** = p < .01; * = p < .05)

Table 34 - Latent class choice models for charity decision with and without additional arousal parameter.

	Without additional par.				With additional par.			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.61		0.39		0.66		0.34	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.20	0.16	-0.20	0.16	0.17	0.17	-0.17	0.17
Living cond. – bad	**3.54*****	1.05	**0.66*****	0.14	**3.66*****	1.05	**0.66*****	0.14
Living cond. – moderate	**-3.54*****		**-0.66*****		**-3.66*****		**-0.66*****	
Family size – 3	-0.95	0.56	**-0.27***	0.12	-0.96	0.56	**-0.27***	0.12
Family size – 6	0.95		**0.27***		0.96		**0.27***	
Will. learn – avg.	**-1.32***	0.56	**-1.19*****	0.14	**-1.33***	0.56	**-1.22*****	0.14
Will. learn – low	**1.32***		**1.19*****		**1.33***		**1.22*****	
Living X Family – diff.	0.63	0.56	0.08	0.14	0.65	0.56	0.10	0.14
Living X Family – same	-0.63		-0.08		-0.65		-0.10	
Living X Learn – diff.	0.36	0.56	0.01	0.12	0.32	0.56	0.01	0.12
Living X Learn – same	-0.36		-0.01		-0.32		-0.01	
Family X Learn – diff.	0.23	1.05	0.04	0.12	0.22	1.05	0.03	0.12
Family X Learn – same	-0.23		-0.04		-0.22		-0.03	
Arousal parameter					-0.22	0.13	0.09	0.10
Statistics								
Nobs	588				588			
No. of parameters	13				15			
LN likelihood	-167.41				-167.03			
BIC	391.24				392.45			
Adj. pseudo-R2(0)	0.82		0.49		0.82		0.50	
Holdout prediction	0.73		0.75		0.73		0.75	

(*** = p < .001; ** = p < .01; * = p < .05)

Table 35 - Latent class choice models for charity decision with and without additional smile-arousal parameter.

	Without additional par.				With additional par.			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.61		0.39		0.60		0.40	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.20	0.16	-0.20	0.16	0.19	0.16	-0.19	0.16
Living cond. – bad	**3.54*** **	1.05	**0.66*** **	0.14	**3.86*** **	1.05	**0.66*** **	0.14
Living cond. – moderate	**-3.54*** **		**-0.66*** **		**-3.86*** **		**-0.66*** **	
Family size – 3	-0.95	0.56	**-0.27***	0.12	-0.99	0.56	**-0.27***	0.12
Family size – 6	0.95		**0.27***		0.99		**0.27***	
Will. learn – avg.	**-1.32***	0.56	**-1.19*** **	0.14	**-1.33***	0.56	**-1.21*** **	0.14
Will. learn – low	**1.32***		**1.19*** **		**1.33***		**1.21*** **	
Living X Family – diff.	0.63	0.56	0.08	0.14	0.62	0.56	0.08	0.14
Living X Family – same	-0.63		-0.08		-0.62		-0.08	
Living X Learn – diff.	0.36	0.56	0.01	0.12	0.34	0.56	0.01	0.12
Living X Learn – same	-0.36		-0.01		-0.34		-0.01	
Family X Learn – diff.	0.23	1.05	0.04	0.12	0.37	1.11	0.05	0.12
Family X Learn – same	-0.23		-0.04		-0.37		-0.05	
Smile-arousal parameter					0.21	0.15	-0.12	0.10
Statistics								
Nobs	588				588			
No. of parameters	13				15			
LN likelihood	-167.41				-166.86			
BIC	391.24				392.11			
Adj. pseudo-R2(0)	0.82		0.49		0.82		0.50	
Holdout prediction	0.73		0.75		0.73		0.75	

(*** = p < .001; ** = p < .01; * = p < .05)

Table 36 - Latent class choice models for charity decision with and without additional frown-arousal parameter.

	Without additional par.				With additional par.			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.61		0.39		0.61		0.39	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.20	0.16	-0.20	0.16	0.19	0.16	-0.19	0.16
Living cond. – bad	**3.54*** **	1.05	**0.66*** **	0.14	**3.56*** **	1.05	**0.66*** **	0.14
Living cond. – moderate	**-3.54*** **		**-0.66*** **		**-3.56*** **		**-0.66*** **	
Family size – 3	-0.95	0.56	**-0.27***	0.12	-0.95	0.56	**-0.30***	0.12
Family size – 6	0.95		**0.27***		0.95		**0.30***	
Will. learn – avg.	**-1.32***	0.56	**-1.19*** **	0.14	**-1.30***	0.56	**-1.25*** **	0.14
Will. learn – low	**1.32***		**1.19*** **		**1.30***		**1.25*** **	
Living X Family – diff.	0.63	0.56	0.08	0.14	0.62	0.56	0.08	0.14
Living X Family – same	-0.63		-0.08		-0.62		-0.08	
Living X Learn – diff.	0.36	0.56	0.01	0.12	0.33	0.56	0.01	0.12
Living X Learn – same	-0.36		-0.01		-0.33		-0.01	
Family X Learn – diff.	0.23	1.05	0.04	0.12	0.17	1.05	0.05	0.12
Family X Learn – same	-0.23		-0.04		-0.17		-0.05	
Frown-arousal parameter					0.03	0.12	0.26	0.12
Statistics								
Nobs	588				588			
No. of parameters	13				15			
LN likelihood	-167.41				-166.68			
BIC	391.24				391.72			
Adj. pseudo-R2(0)	0.82		0.49		0.82		0.52	
Holdout prediction	0.73		0.75		0.73		0.75	

(*** = p < .001; ** = p < .01; * = p < .05)

Table 37 - Latent class choice models for face decision with and without additional smile parameter.

	Without additional par.				With additional par.			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.59		0.41		0.60		0.39	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.18	0.20	-0.18	0.20	0.18	0.20	-0.18	0.20
Eyes – small	**-0.51*** **	0.09	-0.17	0.15	**-0.51*** **	0.09	-0.14	0.15
Eyes – big	**0.51*** **		0.17		**0.51*** **		0.14	
Nose – small	**0.36*** **	0.08	0.12	0.13	**0.36*** **	0.08	0.11	0.13
Nose – big	**-0.36*** **		-0.12		**-0.36*** **		-0.11	
Mouth – small	**0.39*** **	0.12	**-0.77*** **	0.17	**0.37*** **	0.12	**-0.80*** **	0.17
Mouth – big	**-0.39*** **		**0.77*** **		**-0.37*** **		**0.80*** **	
Eyes X Nose – diff.	**-0.17** **	0.08	**-0.31* **	0.14	**-0.17** **	0.08	**-0.33* **	0.14
Eyes X Nose – same	**0.17** **		**0.31* **		**0.17** **		**0.33* **	
Eyes X Mouth – diff.	-0.13	0.08	**-0.27* **	0.11	-0.12	0.08	**-0.27* **	0.11
Eyes X Mouth –same	0.13		**0.27* **		0.12		**0.27* **	
Nose X Mouth – diff.	**0.17** **	0.08	**0.36** **	0.10	**0.17** **	0.08	**0.37** **	0.10
Nose X Mouth – same	**-0.17** **		**-0.36** **		**-0.17** **		**-0.37** **	
Smile parameter					-0.03	0.06	-0.10	0.11
Statistics								
Nobs	588				588			
No. of parameters	13				15			
LN likelihood	-338.97				-338.85			
BIC	728.55				734.81			
Adj. pseudo-R2(0)	0.23		0.36		0.23		0.36	
Holdout prediction	0.09		0.28		0.09		0.28	

(*** = p < .001; ** = p < .01; * = p < .05)

Table 38 - Latent class choice models for face decision with and without additional frown parameter.

	Without additional par.				With additional par.			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.59		0.41		0.66		0.33	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.18	0.20	-0.18	0.20	0.34	0.17	-0.34	0.17
Eyes – small	-0.51***		-0.17		-0.49***		-0.05	
		0.09		0.15		0.09		0.15
Eyes – big	0.51***		0.17		0.49***		0.05	
Nose – small	0.36***		0.12		0.38***		0.05	
		0.08		0.13		0.08		0.15
Nose – big	-0.36***		-0.12		-0.38***		-0.05	
Mouth – small	0.39***		-0.77***		0.29***		-0.98***	
		0.12		0.17		0.12		0.22
Mouth – big	-0.39***		0.77***		-0.29***		0.98***	
Eyes X Nose – diff.	-0.17**		-0.31*		-0.15**		-0.52*	
		0.08		0.14		0.08		0.20
Eyes X Nose – same	0.17**		0.31*		0.15**		0.52*	
Eyes X Mouth – diff.	-0.13		-0.27*		-0.11		-0.40*	
		0.08		0.11		0.08		0.14
Eyes X Mouth –same	0.13		0.27*		0.11		0.40*	
Nose X Mouth – diff.	0.17**		0.36**		0.16**		0.37**	
		0.08		0.10		0.08		0.10
Nose X Mouth – same	-0.17**		-0.36**		-0.16**		-0.37**	
Frown parameter					-0.09	0.06	-0.18	0.12
Statistics								
Nobs	588				588			
No. of parameters	13				15			
LN likelihood	-338.97				-336.61			
BIC	728.55				731.60			
Adj. pseudo-R2(0)	0.23		0.36		0.23		0.36	
Holdout prediction	0.09		0.28		0.09		0.28	

(*** = p < .001; ** = p < .01; * = p < .05)

Table 39 - Latent class choice models for face decision with and without additional arousal parameter.

	Without additional par.				With additional par.			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.59		0.41		0.58		0.41	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.18	0.20	-0.18	0.20	0.17	0.20	-0.17	0.20
Eyes – small	**-0.51*** **	0.09	-0.17	0.15	**-0.51*** **	0.09	-0.17	0.15
Eyes – big	**0.51*** **		0.17		**0.51*** **		0.17	
Nose – small	**0.36*** **	0.08	0.12	0.13	**0.35*** **	0.08	0.13	0.13
Nose – big	**-0.36*** **		-0.12		**-0.35*** **		-0.13	
Mouth – small	**0.39*** **	0.12	**-0.77*** **	0.17	**0.39*** **	0.12	**-0.76*** **	0.17
Mouth – big	**-0.39*** **		**0.77*** **		**-0.39*** **		**0.76*** **	
Eyes X Nose – diff.	**-0.17** **	0.08	**-0.31* **	0.14	**-0.17** **	0.08	**-0.30* **	0.14
Eyes X Nose – same	**0.17** **		**0.31* **		**0.17** **		**0.30* **	
Eyes X Mouth – diff.	-0.13	0.08	**-0.27* **	0.11	-0.13	0.08	**-0.27* **	0.11
Eyes X Mouth –same	0.13		**0.27* **		0.13		**0.27* **	
Nose X Mouth – diff.	**0.17** **	0.08	**0.36** **	0.10	**0.17** **	0.08	**0.36** **	0.10
Nose X Mouth – same	**-0.17** **		**-0.36** **		**-0.17** **		**-0.36** **	
Arousal parameter					-0.03	0.06	0.02	0.09
Statistics								
Nobs	588				588			
No. of parameters	13				15			
LN likelihood	-338.97				-338.84			
BIC	728.55				736.05			
Adj. pseudo-R2(0)	0.23		0.36		0.23		0.36	
Holdout prediction	0.09		0.28		0.09		0.28	

(*** = p < .001; ** = p < .01; * = p < .05)

Table 40 - Latent class choice models for face decision with and without additional frown-arousal parameter.

	Without additional par.				With additional par.			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.59		0.41		0.58		0.41	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.18	0.20	-0.18	0.20	0.16	0.20	-0.16	0.20
Eyes – small	**-0.51*** **	0.09	-0.17	0.15	**-0.50*** **	0.09	-0.18	0.15
Eyes – big	**0.51*** **		0.17		**0.50*** **		0.18	
Nose – small	**0.36*** **	0.08	0.12	0.13	**0.36*** **	0.08	0.13	0.13
Nose – big	**-0.36*** **		-0.12		**-0.36*** **		-0.13	
Mouth – small	**0.39*** **	0.12	**-0.77*** **	0.17	**0.40*** **	0.12	**-0.76*** **	0.17
Mouth – big	**-0.39*** **		**0.77*** **		**-0.40*** **		**0.76*** **	
Eyes X Nose – diff.	**-0.17** **	0.08	**-0.31* **	0.14	**-0.17** **	0.08	**-0.30* **	0.14
Eyes X Nose – same	**0.17** **		**0.31* **		**0.17** **		**0.30* **	
Eyes X Mouth – diff.	-0.13	0.08	**-0.27* **	0.11	-0.13	0.08	**-0.27* **	0.11
Eyes X Mouth –same	0.13		**0.27* **		0.13		**0.27* **	
Nose X Mouth – diff.	**0.17** **	0.08	**0.36** **	0.10	**0.17** **	0.08	**0.37** **	0.10
Nose X Mouth – same	**-0.17** **		**-0.36** **		**-0.17** **		**-0.37** **	
Frown-arousal parameter					-0.01	0.06	-0.06	0.08
Statistics								
Nobs	588				588			
No. of parameters	13				15			
LN likelihood	-338.97				-338.66			
BIC	728.55				735.71			
Adj. pseudo-R2(0)	0.23		0.36		0.23		0.36	
Holdout prediction	0.09		0.28		0.09		0.28	

(*** = p < .001; ** = p < .01; * = p < .05)

Table 41 - Latent class choice models for yogurt decision with and without additional frown parameter.

	Without additional par.				With additional par.			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.58		0.42		0.58		0.42	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.14	0.15	-0.14	0.15	0.12	0.15	-0.12	0.15
Taste – apricot	**-0.68*** **	0.10	**0.51*** **	0.17	**-0.69*** **	0.10	**0.49*** **	0.14
Taste – strawberry	**0.68*** **		**-0.51*** **		**0.69*** **		**-0.49*** **	
Fat content – 1.5%	**0.50*** **	0.12	**-0.61*** **	0.13	**0.52*** **	0.12	**-0.59*** **	0.12
Fat content – 3.5%	**-0.50*** **		**0.61*** **		**-0.52*** **		**0.59*** **	
Label – best standard	**-0.47*** **	0.10	**-0.82*** **	0.16	**-0.47*** **	0.10	**-0.80*** **	0.13
Label – organic	**0.47*** **		**0.82*** **		**0.47*** **		**0.80*** **	
Taste X Fat content – diff.	-0.09	0.08	-0.03	0.13	-0.10	0.08	-0.01	0.12
Taste X Fat content – same	0.09		0.03		0.10		0.01	
Taste X Label – diff.	0.01	0.08	-0.06	0.13	0.01	0.08	-0.05	0.11
Taste X Label – same	-0.01		0.06		-0.01		0.05	
Fat content X Label – diff.	-0.01	0.08	0.07	0.13	-0.01	0.08	0.06	0.12
Fat content X Label – same	0.01		-0.07		0.01		-0.06	
Frown parameter					0.06	0.07	0.12	0.08
Statistics								
Nobs	588				588			
No. of parameters	13				15			
LN likelihood	-314.78				-313.30			
BIC	680.15				684.99			
Adj. pseudo-R2(0)	0.33		0.39		0.34		0.32	
Holdout prediction	0.50		0.57		0.50		0.57	

(*** = p < .001; ** = p < .01; * = p < .05)

Table 42 - Latent class choice models for yogurt decision with and without additional arousal parameter.

	Without additional par.				With additional par.			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.58		0.42		0.59		0.40	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.14	0.15	-0.14	0.15	0.12	0.15	-0.12	0.15
Taste – apricot	**-0.68*** **	0.10	**0.51*** **	0.17	**-0.65*** **	0.10	**0.62*** **	0.18
Taste – strawberry	**0.68*** **		**-0.51*** **		**0.65*** **		**-0.62*** **	
Fat content – 1.5%	**0.50*** **	0.12	**-0.61*** **	0.13	**0.45*** **	0.12	**-0.68*** **	0.18
Fat content – 3.5%	**-0.50*** **		**0.61*** **		**-0.45*** **		**0.68*** **	
Label – best standard	**-0.47*** **	0.10	**-0.82*** **	0.16	**-0.47*** **	0.10	**-0.89*** **	0.15
Label – organic	**0.47*** **		**0.82*** **		**0.47*** **		**0.89*** **	
Taste X Fat content – diff.	-0.09	0.08	-0.03	0.13	-0.09	0.08	-0.10	0.15
Taste X Fat content – same	0.09		0.03		0.09		0.10	
Taste X Label – diff.	0.01	0.08	-0.06	0.13	0.01	0.08	-0.12	0.16
Taste X Label – same	-0.01		0.06		-0.01		0.12	
Fat content X Label – diff.	-0.01	0.08	0.07	0.13	-0.02	0.08	0.12	0.17
Fat content X Label – same	0.01		-0.07		0.02		-0.12	
Arousal parameter					-0.03	0.07	0.16	0.11
Statistics								
Nobs	588				588			
No. of parameters	13				15			
LN likelihood	-314.78				-313.36			
BIC	680.15				685.11			
Adj. pseudo-R2(0)	0.33		0.39		0.31		0.35	
Holdout prediction	0.50		0.57		0.50		0.57	

(*** = p < .001; ** = p < .01; * = p < .05)

Table 43 - Latent class choice models for yogurt decision with and without additional smile-arousal parameter.

	Without additional par.				With additional par.			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.58		0.42		0.57		0.43	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.14	0.15	-0.14	0.15	0.15	0.16	-0.15	0.16
Taste – apricot	**-0.68*** **	0.10	**0.51*** **	0.17	**-0.69*** **	0.10	**0.52*** **	0.17
Taste – strawberry	**0.68*** **		**-0.51*** **		**0.69*** **		**-0.52*** **	
Fat content – 1.5%	**0.50*** **	0.12	**-0.61*** **	0.13	**0.51*** **	0.12	**-0.61*** **	0.13
Fat content – 3.5%	**-0.50*** **		**0.61*** **		**-0.51*** **		**0.61*** **	
Label – best standard	**-0.47*** **	0.10	**-0.82*** **	0.16	**-0.49*** **	0.10	**-0.80*** **	0.15
Label – organic	**0.47*** **		**0.82*** **		**0.49*** **		**0.80*** **	
Taste X Fat content – diff.	-0.09	0.08	-0.03	0.13	-0.10	0.08	-0.04	0.13
Taste X Fat content – same	0.09		0.03		0.10		0.04	
Taste X Label – diff.	0.01	0.08	-0.06	0.13	0.05	0.08	-0.06	0.13
Taste X Label – same	-0.01		0.06		-0.05		0.06	
Fat content X Label – diff.	-0.01	0.08	0.07	0.13	-0.02	0.08	0.07	0.13
Fat content X Label – same	0.01		-0.07		0.02		-0.07	
Smile-arousal parameter					-0.09	0.06	0.11	0.16
Statistics								
Nobs	588				588			
No. of parameters	13				15			
LN likelihood	-314.78				-312.76			
BIC	680.15				683.90			
Adj. pseudo-R2(0)	0.33		0.39		0.31		0.35	
Holdout prediction	0.50		0.57		0.50		0.57	

(*** = p < .001; ** = p < .01; * = p < .05)

Table 44 - Latent class choice models for yogurt decision with and without additional frown-arousal parameter.

	Without additional par.				With additional par.			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.58		0.42		0.56		0.44	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.14	0.15	-0.14	0.15	0.15	0.16	-0.15	0.16
Taste – apricot	**-0.68*****	0.10	**0.51*****	0.17	**-0.69*****	0.10	**0.49*****	0.15
Taste – strawberry	**0.68*****		**-0.51*****		**0.69*****		**-0.49*****	
Fat content – 1.5%	**0.50*****	0.12	**-0.61*****	0.13	**0.51*****	0.12	**-0.60*****	0.12
Fat content – 3.5%	**-0.50*****		**0.61*****		**-0.51*****		**0.60*****	
Label – best standard	**-0.47*****	0.10	**-0.82*****	0.16	**-0.48*****	0.10	**-0.80*****	0.14
Label – organic	**0.47*****		**0.82*****		**0.48*****		**0.80*****	
Taste X Fat content – diff.	-0.09	0.08	-0.03	0.13	-0.10	0.08	-0.02	0.12
Taste X Fat content – same	0.09		0.03		0.10		0.02	
Taste X Label – diff.	0.01	0.08	-0.06	0.13	0.01	0.08	-0.05	0.12
Taste X Label – same	-0.01		0.06		-0.01		0.05	
Fat content X Label – diff.	-0.01	0.08	0.07	0.13	-0.01	0.08	0.06	0.12
Fat content X Label – same	0.01		-0.07		0.01		-0.06	
Frown-arousal parameter					-0.05	0.07	-0.03	0.09
Statistics								
Nobs	588				588			
No. of parameters	13				15			
LN likelihood	-314.78				-314.49			
BIC	680.15				687.37			
Adj. pseudo-R2(0)	0.33		0.39		0.33		0.39	
Holdout prediction	0.50		0.57		0.50		0.57	

(*** = p < .001; ** = p < .01; * = p < .05)

Appendix F - Latent class choice models with non-significant discrete affect parameters

Tables start on next page due to table size.

Table 45 - Latent class choice models for charity decisions without and with discrete affect parameters based on arousal and smile muscle activity or arousal and frown muscle activity.

	Behavioral				Discrete affect based on smile				Discrete affect based on frown			
	Class 1		Class 2		Class 1		Class 2		Class 1		Class 2	
Class size	0.61		0.39		0.60		0.40		0.59		0.41	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.20	0.16	-0.20	0.16	0.19	0.15	-0.19	0.15	0.18	0.15	-0.18	0.15
Living cond. – bad	**3.54*** **	1.05	**0.66*** **	0.14	**4.16*** **	1.38	**0.71*** **	0.14	**4.22*** **	1.49	**0.72*** **	0.14
Living cond. – moderate	**-3.54*** **		**-0.66*** **		**-4.16*** **		**-0.71*** **		**-4.22*** **		**-0.72*** **	
Family size – 3	-0.95	0.56	**-0.27***	0.12	-1.66	0.57	**-0.22***	0.13	-1.80	1.33	**-0.25***	0.13
Family size – 6	0.95		**0.27***		1.66		**0.22***		1.80		**0.25***	
Will. learn – avg.	**-1.32***	0.56	**-1.19*** **	0.14	**-1.40***	0.57	**-1.21*** **	0.16	**-1.36***	0.57	**-1.25*** **	0.16
Will. learn – low	**1.32***		**1.19*** **		**1.40***		**1.21*** **		**1.36***		**1.25*** **	
Living X Family – diff.	0.63	0.56	0.08	0.14	0.61	0.56	0.13	0.15	0.63	0.56	0.11	0.15
Living X Family – same	-0.63		-0.08		-0.61		-0.13		-0.63		-0.11	
Living X Learn – diff.	0.36	0.56	0.01	0.12	0.29	0.56	0.06	0.14	0.30	0.56	0.08	0.14
Living X Learn – same	-0.36		-0.01		-0.29		-0.06		-0.30		-0.08	
Family X Learn – diff.	0.23	1.05	0.04	0.12	0.98	1.54	0.01	0.12	1.08	1.62	0.03	0.12
Family X Learn – same	-0.23		-0.04		-0.98		-0.01		-1.08		-0.03	
Anger					0.44	0.51	-0.17	0.11	0.46	0.59	-0.15	0.11
Joy					0.42	0.53	-0.01	0.11	0.53	0.58	-0.06	0.11
Sadness					0.07	0.52	0.10	0.10	0.34	0.60	0.18	0.11
Contentment					0.34	0.54	-0.05	0.11	0.25	0.58	-0.15	0.10
Statistics												
Nobs	588				588				588			
No. of parameters	13				21				21			
LN likelihood	-167.41				-164.19				-162.93			
BIC	391.24				410.11				407.59			
Adj. pseudo-R^2(0)	0.82		0.49		0.83		0.51		0.83		0.57	
Holdout prediction	0.73		0.75		0.73		0.75		0.73		0.75	

(*** = p < .001; ** = p < .01; * = p < .05)

Table 46 - Latent class choice models for yogurt decisions without and with discrete affect parameters based on arousal and frown muscle activity.

	Behavioral				Discrete affect based on frown			
	Class 1		Class 2		Class 1		Class 2	
Class size	0.58		0.42		0.56		0.43	
	Par.	SE	Par.	SE	Par.	SE	Par.	SE
Class intercepts	0.14	0.15	-0.14	0.15	0.14	0.16	-0.14	0.16
Taste – apricot	**-0.68*** **	0.10	**0.51*** **	0.17	**-0.73*** **	0.11	**0.52** **	0.17
Taste – strawberry	**0.68*** **		**-0.51*** **		**0.73*** **		**-0.52** **	
Fat content – 1.5%	**0.50*** **	0.12	**-0.61*** **	0.13	**0.53** **	0.14	**-0.57** **	0.14
Fat content – 3.5%	**-0.50*** **		**0.61*** **		**-0.53** **		**0.57** **	
Label – best standard	**-0.47*** **	0.10	**-0.82*** **	0.16	**-0.42*** **	0.09	**-0.81** **	0.15
Label – organic	**0.47*** **		**0.82*** **		**0.42*** **		**0.81** **	
Taste X Fat content – diff.	-0.09	0.08	-0.03	0.13	-0.10	0.09	-0.10	0.09
Taste X Fat content – same	0.09		0.03		0.10		0.10	
Taste X Label – diff.	0.01	0.08	-0.06	0.13	-0.02	0.10	-0.02	0.10
Taste X Label – same	-0.01		0.06		0.02		0.02	
Fat content X Label – diff.	-0.01	0.08	0.07	0.13	-0.01	0.09	-0.01	0.09
Fat content X Label – same	0.01		-0.07		0.01		0.01	
Anger					-0.09	0.08	-0.10	0.09
Joy					-0.03	0.08	0.01	0.10
Sadness					0.03	0.08	0.02	0.09
Contentment					0.09	0.08	-0.08	0.09
Statistics								
Nobs	588				588			
No. of parameters	13				21			
LN likelihood	-314.78				-312.04			
BIC	680.15				705.81			
Adj. pseudo-R2(0)	0.33		0.39		0.33		0.39	
Holdout prediction	0.50		0.57		0.50		0.60	

(*** = p < .001; ** = p < .01; * = p < .05)

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(Format follows APA 6th style)

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